

Motor Imagery-based BCI Perspective in Procedure and Analysis

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Abstract. Motor Imagery (MI) is a cognitive exercise that can be utilized in motor rehabilitation. Using brain-computer interfaces (BCIs) is a practical technique to link computers and human brains, which can acquire and understand human brain signals when performing. MI-BCI has been proven effective to help the paralyzed regain basic movement controls. However, some problems are hindering the development of MI-BCI. Predecessors have proposed relevant methods to resolve them. Thus, it is important to learn about MI-BCI comprehensively and understand some novel methods to improve the performance of MI-BCI. Collecting and reviewing other essays, the study focuses on the structure and lists new applications of MI-BCI especially about the use of deep learning. The study also discusses self-paced training during the calibration phase and deep learning approaches for potential fields. Finally, the analysis of applications and four possible future directions are posed in the discussion, hoping to offer some useful advice to improve MI-based BCI.

Keywords: Brain-Computer Interface (BCI), Motor Imagery (MI), Deep Learning.

1. Introduction

Motor Imagery (MI) is a cognitive exercise allowing people to imagine their movements in their minds without execution. Recent studies have shown that MI can effectively treat neurological damage in paraplegic patients, including those who have suffered a stroke [1]. The patients suffering from stroke have great difficulty moving their upper and lower limbs, which can severely damage their life qualities. However, MI is hard to manage and manifest due to its intangible and invisible properties. Brain-computer interfaces (BCIs) can bridge the gap between humans and machines, and provide cerebral feedback which can present the state of the movements. Thus, BCI can work to help patients perform MI tasks and guide them to concentrate on imaginary movements, providing a new perspective of treatment for motor rehabilitation called MI-based BCI. MI-BCI has been proved to be an emerging therapy in neurorehabilitation and can facilitate the life of disabled patients [2].

To detect cerebral signals and control the BCI system, real-time electroencephalogram (EEG) has been introduced to the MI-BCI technique for many years and demonstrated its practicality in MI-BCI for motor rehabilitation [3]. Nowadays, EEG and MI-BCI have formed a typical and reliable scientific mode for further studying. The common method of processing MI-EEG signals mainly involves three parts: preparing and data preprocessing feature extraction, and classification and evaluation. Each procedure consists of several steps, which the paper will summarize in the following sections. What's more, high performance of signal classification and calibration is of great importance in MI-BCI systems. However, the traditional methods for EEG classification and calibration are not that perfect. As a relatively novel design, MI-BCI design has two crucial problems to tackle: 1) specific MI-EEG signals from brains are always complex to possess and decode because they are easily influenced by a variety of noise sources, such as biological artifacts, electronic equipment, and environmental noise [4]. It is worth discussing whether to make changes based on the original structure or to introduce new processing approaches. 2) The calibration time (usually 20-30 minutes) before using is long but necessary. The calibration stage is a crucial prerequisite for MI-BCI work, however it cannot be denied that the currently popular calibration approach takes a while and might easily have a negative affect on subjects. This reduces the method's viability. The long time will increase the mental burden of users and cause psychological fatigue such as the loss of energy and difficulty in concentrating [5].

Nevertheless, MI-BCI can be an innovative and promising approach for motor rehabilitation, focusing on the sport restoration of upper and lower limbs. Recently, an increasing number of studies have fully made use of the practice of MI tasks and BCI systems to help patients regain basic movement control, among which different methods are put in use. The researchers built the MI-BCI rehabilitation system and utilised it to manipulate the robotic arm and carry out some simple arm movements, which is helpful for patient rehabilitation [6]. On the other hand, Electric Stimulation (ES) can be combined with MI-BCI to cure patients' lower limbs, which can generate currents to excite damaged nerves of the paralyzed [7].

Actually, plenty of reviews have been published but most of them are complicated and obscure, which is not suitable for freshmen to know MI-BCI comprehensively. Consequently, this study tries to summarize MI-BCI precisely and explicitly. This paper reviews the essays about MI-based BCI, clarifies the structure of the MI-EEG-BCI system, poses novel scientific methods to solve the problem proposed above, and further analyzes arising difficulties after applying new techniques. Finally, some possible future directions to improve MI-BCI are illustrated as well. The general flow of the paper is shown in Figure 1.

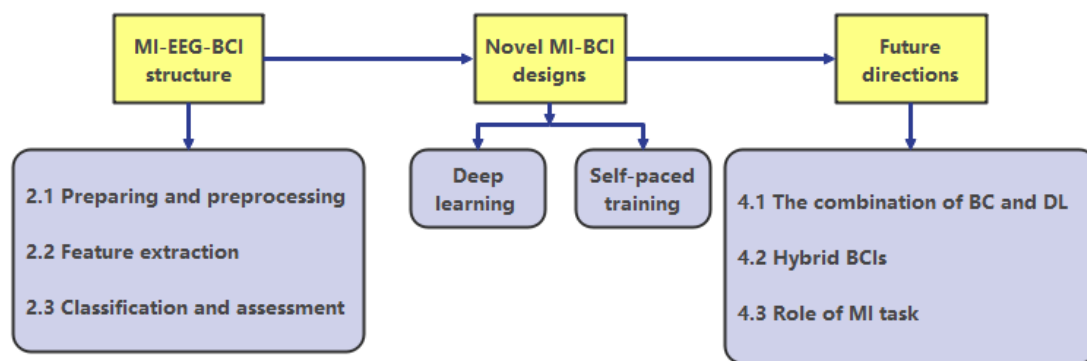


Figure 1. Each part's content and structure in this study

2. Related works

2.1. MI-based BCI using EEG

2.1.1 Preparing and preprocessing

Brain signals can be converted to EEG to convey messages such as movements to researchers and users. In typical BCI-EEG experiments, electrodes, which are also called EEG channels, can be placed on users' heads and connect with the skin. The electrical activity of brain nerves can be collected by EEG, which can also enhance the signals to create predictable patterns that correspond to various mental states. EEG can therefore be used to record and pick the precise patterns that researchers are interested in.

To produce specific patterns of MI tasks, users have to go through the calibration phase. The most-used calibration method is the Graz paradigm where the users should complete MI activities while a cue is delivered. An example is shown in Figure 2. The calibration usually contains a series of repeated sessions. In this way, the BCI system can distinguish different EEG images based on different MI tasks. However, the calibration phase should last for 20 to 30 minutes, leading to additional fatigue for users. For instance, mental fatigue can reduce MI-BCI performance in patients with motor deficits [5].

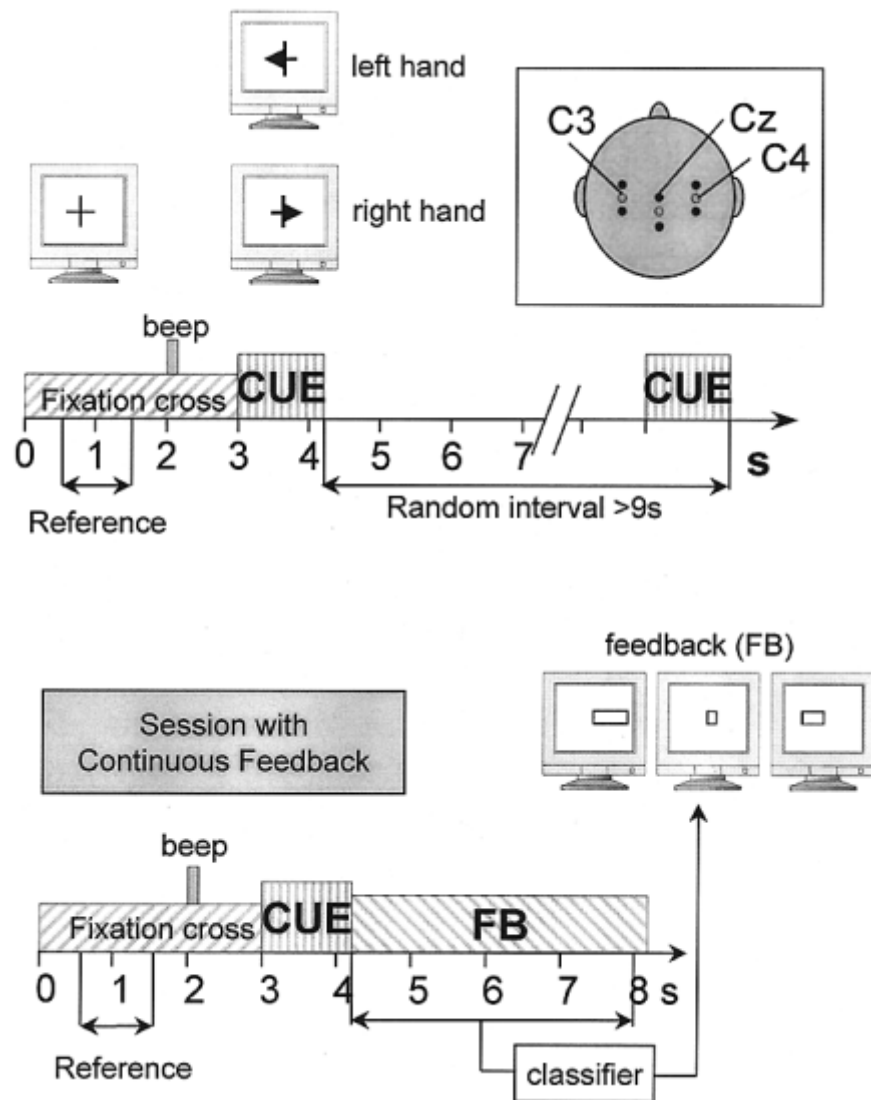


Figure 2. A typical experiment using the Graz paradigm. The direction of the arrow was shown to refer to the left- or right-hand movement [8].

After users modulate the MI-BCI task during the calibration time, the researchers must collect and decode distinct EEG signals from the brain formally. Artifacts can be a vital barrier to selecting the targeted EEG patterns. They are the noise that is irrelevant to the wanted brain activities, generally divided into internal (eg., heartbeats and eye blink) and external artifacts (eg., sounds and wires) [9]. To remove annoying artifacts, researchers will filter the signals according to different brain oscillations related to diverse MI tasks, which served as a critical process in signal preprocessing.

2.1.2 Feature extraction

When users perform MI tasks, a variety of data can be gathered, generating mountains of values, which contributes to the complexity of MI-BCI. Therefore, the experimenters need to select some unnoticeable but specific values representing ongoing MI tasks executed by users. That is what feature extraction during MI-BCI means. One significant problem to feature extraction is how to gather and handle a huge amount of data in a BCI system. As a result, applying dimension reduction approaches can be labor-saving [10]. Without these methods, processing massive and complex data can be a daunting and time-consuming task.

To attain precise results, people have carried out various methods used in feature extraction including utilizing common spatial patterns (CSP), short-time Fourier transform (STFT), statistical features, band power and so on [9]. Among them, the prevalent ways are extracting power spectral density (PSD), differential entropy (DE), or complexity via time frequency. As is seen in Figure 3,

employing other approaches to further refine the results can be useful. Therefore, feature extraction is worth investigating and developing. To be honest, feature extraction is a complex and multistep process, however, the paper just summarizes the core.

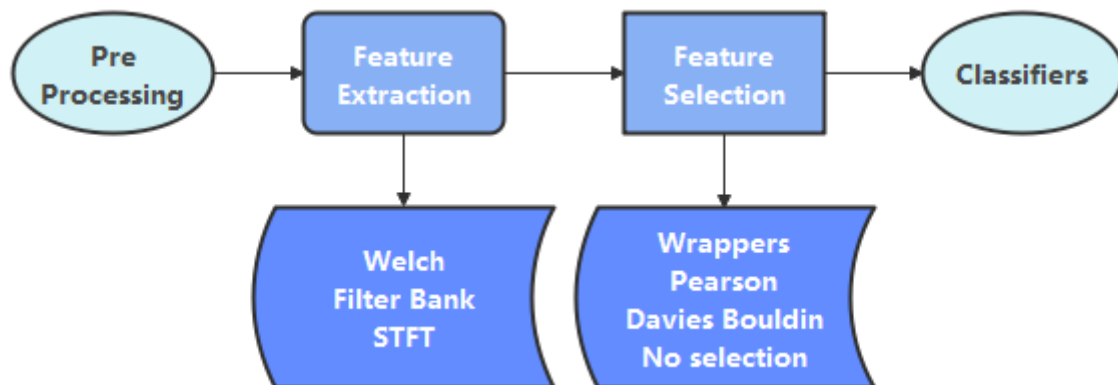


Figure 3. Several methods used for feature extraction and selection [11].

2.1.3 Classification and assessment

In classification, different algorithms work to classify the features more precisely. In short, classification is a further phase to process the selected feature, allowing researchers to achieve high performance of MI-BCI [9]. To evaluate and raise the standards of MI-BCI tasks, accuracy is treated as a prominent value to measure the performance of MI-based BCI. A previous study reported relevant classification accuracy of different MI strategies in order to treat Parkinson's disease and succeed in screening the best MI-BCI approach [12]. Apart from accuracy, the participants' ability to mediate their brain signals can be another assessment of the MI-BCI effect [13]. Thus, on account of individual or groups scientific goals, the assessment methods can vary but have similarities in total. We can select the most appropriate and effective MI-BCI approach and, based on the outcomes, modify the current method by evaluating the efficacy of other MI-BCI modes.

Although the aforementioned scientific investigations have offered a general fundamental model of MI-BCI, it has been a research hotspot of concern to figure out how to develop advancements and innovations in the original structure. Among them, how to better process and screen massive and complex data is one of the key links.

2.2. Novel MI-BCI techniques and designs: from classification to calibration

In this section, the paper will propose some emerging MI-BCI designs to improve EEG signals classification and calibration phase. On one hand, the deep learning technique (eg., CNN) has gained increasing popularity in recent years to become a new signal classification method. On the other hand, transfer learning can greatly reduce calibration time and with self-paced training, the traditional calibration approach (eg., the Graz paradigm) can be replaced, which is bound to perfect the MI-BCI experience. The following text will elaborate on these techniques further.

Deep learning (DL) dedicates to modeling and predicting the numerous brain states to process mountains of messages and data [14]. Compared with the traditional ways to classify MI-EEG signals, which are easy to be affected by unnecessary noise and are more empirical, DL can automatically capture the features from raw MI-EEG signals and produce satisfying results after enough training. A study analyzed relevant resources to further identify and evaluate the classification capacity of DL. Based on their study, DL can reduce the preprocessing greatly but still reach high accuracy for MI classification. Also, artifact removal is probably not that important to DL, which needs to be further investigated [4]. Thus, the use of DL can contribute to brain signal classification considerably.

One of the deep learning techniques, convolution neural network (CNN), is gaining popularity among scientists. Scientists utilized CNN classifier to assess MI signals and the results reached high accuracy in multi-class MI classification. In their work, they made use of CNN to enhance the ability of classification in MI-BCI [15]. Jeonghyun Kim et al. improved CNN to categorize MI-EEG signals

by extracting magnitude and phase parameters. Based just on magnitude information, the results showed that the novel strategy could be more effective than other methods [16]. Many scientists work on CNN methods to put forward a more handy and high-efficiency protocol for MI task classification.

Transfer learning (TL) is another use of deep learning techniques. It is also an effective way to improve signal classification in MI-BCI. Employing different principles, transfer learning methods can be various, such as Euclidean alignment (EA) and transfer component analysis (TCA). What's more, TL can provide greater classification performance when combined with other techniques such as spatial filtering, showing it has great potential to be further exploited [17].

In addition to improving MI-BCI's accuracy, the method has been suggested as a workable answer to the lengthy calibration process. For example, Laura Ferrero et al. proposed a novel calibration schema that utilized transfer learning. Besides, to sustain the training effect, they used virtual reality (VR) to guide participants to perform well. In addition to the shorter calibration phase, participants could provide better performance when transfer learning was applied. However, changes in EEG properties were likely to interfere with the test results [18]. Besides, a new transfer learning method, which is a hybrid of Euclidean alignment and transfer component analysis, has been proved to provide better performance than conventional TL methods in the calibration phase. Interestingly, the classification accuracy outdid the proposed approaches in the experiment [19]. To sum up, transfer learning can be used to reduce the calibration time, which may cause people's fatigue, and improve MI-BCI performance.

There is also another way to eliminate MI-BCI calibration. In the study carried out by Seon-Min Kim et. al., a new method, which can replace the conventional calibration phase, had been proved effective. It is called self-paced training, allowing participants to perform MI tasks freely in just one minute. They also improved the feature extraction method while recording EEG signals. Although the classification performance of self-paced training was slightly weaker than the conventional calibration method, neither approach significantly differed from the other in terms of classification accuracy. Also, self-paced training could reach high performance in a short time [20]. Apparently, the proposed method is likely to be an efficient and reliable one to take place of the conventional calibration process, reducing users' distraction and exhaustion. Thus, it can improve the MI-BCI system's usefulness in actual situations. The concept of self-paced training can be used for different purposes, including artifact removal [21], but there is not much research on how to apply this technique to the calibration phase, which needs more experiments and validations.

In a nutshell, DL techniques, including CNN and TL, can be widely used in classification and calibration phases, reducing the difficulty of distinguishing feature data and enhancing the effect of MI-BCI and the accuracy of results. Self-paced training, as a new strategy for calibration, can be really potential in the future.

3. Discussion

The article has elucidated the typical structure of MI-BCI and the statement has listed a series of applications, emphatically focused on DL techniques, to enhance signals classification and reduce calibration time. To develop MI-BCI, people have introduced a variety of applications and gained a lot of experience. However, there are still some limitations that impede MI-based BCI improvement. Herein, the section will analyze the current situation and pose relevant future directions to better resolve the problems.

Although predecessors have studied MI-BCI in different ways and a lot of experiments have been carried out, there is still something to improve. Those can be summarized as follows: 1) how to process high-dimension data effectively while maintaining excellent classification ability (eg., in deep learning techniques). It is well known that as the processing of data becomes more difficult, the methods used should correspondingly become more sensitive and easier to manipulate. 2) how to avoid the drawbacks of EEG which is non-stationary and sensitive to additional noise. One issue that needs to be addressed in scientific study is how to make the EEG signal stable in a range of

contexts and how to increase the reliability of the derived data. 3) how MI works and how MI affects the performance of BCI. Additional thought should be given to the distinctions between various types of MI and if the outcome is consistent. To retain the optimum effect, it's crucial to assign particular MI jobs to different people. Thus, to answer the question, the paper proposes following future directions to improve MI-BCI.

3.1. The combination of brain connectivity and deep learning

Previous studies have demonstrated deep learning can be widely used to process a huge quantity of data from the brain. Relevant applications such as CNN and TL can contribute to MI classification and calibration strikingly, and many institutions research these to create and consummate their inventions. However, DL may also be paired with another novel characteristic. That is brain connectivity (BC), which entails investigating and establishing relationships between various brain regions to more accurately represent dynamic information flow patterns. In fact, during MI activities, various brain regions function as a whole while sending information. Furthermore, it is essential to take connection patterns into account while categorizing MI signals. Thus, despite its limitations, BC can be a valuable piece of evidence for the state of a particular brain and for human thought. When combined with BC, DL can decode data with high complexity and perform better, and BC can also be considerably enhanced and employed at the same time [14]. However, BC-DL lacks further experiments to validate its feasibility and performance during MI tasks.

3.2. Hybrid BCIs

Most of the studies analyzed in the paper focus on the unimodal approach of MI-BCI. But it can restrict its MI task classification ability by only relying on EEG signals, which can extract limited feature information due to its non-stationary quality and negative impact of noise. Thus, how to build up the multimodal methods of MI-BCI can be a fresh line of inquiry to enhance MI-BCI performance. To identify complicated brain information in BCI, for example, EEG can be paired with functional near-infrared spectroscopy (fNIRS) [22]. Additionally, a hybrid MI-BCI system can make significant contributions to asynchronous BCIs by offering users a useful approach to controlling devices according to their own preferences, which is presented in Figure 4.

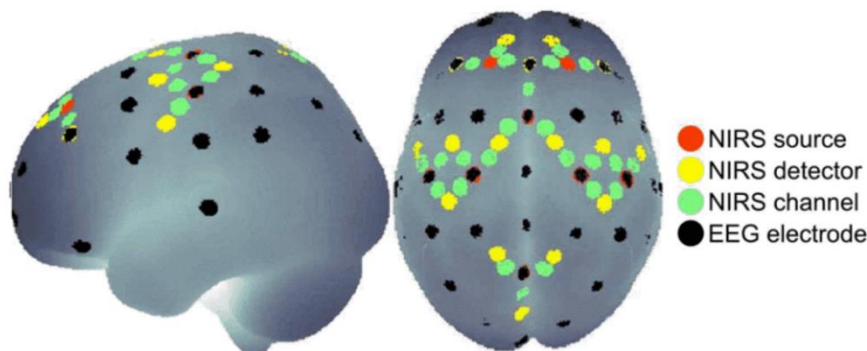


Figure 4. The EEG-NIRS system configuration [23].

Apart from that, MI-BCI and transient visual evoked potentials can form a novel hybrid system for motor rehabilitation. The research showed the method can reach high recognition accuracy [24]. The hybrid BCIs can handle more complex information, apply to a wider range of situations, and improve its signal recognition function through a number of measurements. The methods may be a powerful tool for processing massive amounts of data. Hence, exploring hybrid BCIs more is a promising direction to develop MI-BCI.

3.3. Role of MI task

To boost the effectiveness of MI-BCI, numerous research have thoroughly analyzed and categorized MI algorithms. Apart from algorithms, the study also showed a strong correlation

between the quality of the MI task and MI-BCI performance. However, there is little survey on the MI task itself, leaving some questions such as what kinds of MI tasks are, all the MI tasks suitable for the BCI system, and how to choose different types of MI tasks. Thus, it is of great significance to determine how MI tasks affect the BCI system and classify specific features of different MI tasks. There are mainly two types of MI and the first one is kinesthetic motor imagery (KMI). KMI is for first-person perspective, allowing people to imagine the movements in their brains without actual action. The other one is visual motor imagery (VMI). VMI is for a third-person perspective, guiding people to visualize the presence of the movements in their minds. During KMI or VMI, different brain regions are stimulated at different levels and the difficulty of the task varies [25].

Accordingly, how to evaluate the performance of MI tasks properly and test the suitability can be a crucial topic for scientists. Generally, people can acquire the information via professional questionnaires such as movement imagery questionnaire (MIQ). In this way, subjects' ability to master MI tasks can be assessed. In addition, EEG can be used to extract the features of cerebral patterns while performing MI tasks and evaluate brain activation. Finally, the results can help participants choose the best MI-BCI strategies [25]. But it is an area lacking deeper investigation and verification, which is also a possible way to improve MI-based BCI. Thus, the procedure of MI-BCI can be updated, which is shown in Figure 5.

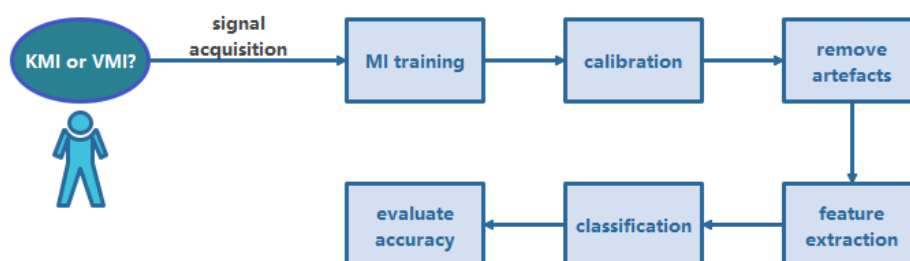


Figure 5. The updated flow of the MI-BCI combining the assessment of MI tasks and typical MI-based BCI structure

Additionally, the studies mentioned above, however, are limited to investigations and tests on small samples, and many participants are actually not paralyzed. Therefore, it remains to be seen whether MI-BCI works well in larger subjects and patients. The MI-BCI subjects were also in a relatively homogeneous environment with less outside interference, which may not be conducive to testing whether the technique performs well in real life as well. How much effect MI-BCI can have on the recovery of exercise is a question that we need to continue to study. As a new treatment for patients with paralysis, the problems it faces are challenging. This approach could also be improved in several ways but research suggests that MI-BCI could be a useful medical tool for assisting patients in progressively regaining their capacity for activity.

4. Conclusion

MI-BCI is being used to treat patients with motor deficits more frequently these days. It offers the globe a fresh viewpoint on how to address the neurorehabilitation issue. The typical structure of MI-BCI and some innovative techniques to enhance the performance of MI-BCI have been summarized. It is obvious to find that DL techniques, such as CNN network and TL, can play an important role in both classification and calibration and self-paced training can be used to accelerate the process, making MI-BCI a more efficient and convenient therapy for patients with motor deficits. However, there are limited experiments on the self-paced training used in calibration. To guide the freshmen to know MI-based BCI comprehensively and accessibly, the review can introduce a general flow of MI-BCI and pose some popular research orientations, especially for the improvement of signal classification and calibration during MI-BCI.

At the end of the paper, some possible future directions are also put forward to explore more possibilities in MI-BCI, including the use of BC, hybrid BCIs, and the implications and measurements of MI tasks. Therefore, this paper introduces the specific contents of each direction and expounds on the relevant experimental progress. Although the implementation of these innovations seems quite hopeful, more experiments and demonstrations are needed. Despite the fact that most studies have concentrated on straightforward hand or leg motions, few techniques have been proven to work for more intricate motions. As a result, the processing of more diverse and complicated data benefits from the innovation and advancement of research methodologies as well as the flexible mixing of multiple methods. Although this work describes the fundamentals of MI-BCI and covers several cutting-edge applications, it does not delve deeply enough into the essentials because of its length and the cognitive understanding requirements. As a result, future studies will continue to explore these issues in greater depth and make a more thorough inclusion. If possible, the study will work to conduct additional research into the direction of the associated MI-future BCI's research and develop a creative plan that meets expectations.

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