Engineering 7 (2021) 1710–1712

Contents lists available at ScienceDirect

Engineering

journal homepage: www.elsevier.com/locate/eng

Views & Comments

Current Challenges for the Practical Application of Electroencephalography-Based Brain–Computer Interfaces

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It has been almost 50 years since the term "brain–computer interface" (BCI) was first proposed by Jacques J. Vidal in 1973 [1]. Unlike traditional electronic interfaces that transmit nonliving information between devices, BCIs set up a communication bridge between a living brain and nonliving devices. Technically speaking, a BCI is a system that measures brain activity and converts it into the artificial outputs that replace, restore, enhance, supplement, or improve the natural central nervous system outputs [2]. At present, electroencephalography (EEG) is the most commonly used brain signal for BCIs.

From the perspective of electronic communications, the two most important issues for EEG-based BCIs are the encoding strategy that converts a person's thoughts into detectable EEG signals, which is usually called a paradigm in the BCI field, and the decoding strategy that extracts and recognizes EEG features, which is called an algorithm. Therefore, the information transfer rate (ITR) is a key index that is widely used in communication systems for evaluating the encoding and decoding efficiency of a BCI. The last decade has witnessed an enormous ITR increase in BCIs. More specifically, the largest bitrate was only approximately 1.5 bits per second (bps) around 2010 [3], but it tripled in 2015 [4] and recently reached about 7 bps [5].

From another point of view, a BCI can be regarded as a processor, which processes the commands requested by the user. Therefore, it is indispensable to evaluate the BCI command processing manner and its capacity. A clear indicator is how many different commands a BCI can process—that is, the size of the command set. In the past ten years, the number of BCI commands has grown remarkably, increasing from about 30 in 2010 to over 100 in 2020 [6]. Another important indicator is whether BCIs can be operated using an asynchronous method. However, this field is still underdeveloped.

Aside from these two perspectives, a BCI is also an instrument for measuring mental activity. Unlike traditional measuring instruments, such as EEG amplifiers that merely detect the EEG signal itself, BCIs detect the psychological process lying behind the signal, such as the occurrence of left- versus right-hand motor imagery activity. Thus, the measurement precision of a BCI is equivalent to the smallest EEG feature that can be decoded and interpreted in real time. The smaller the signal decoded by the BCI, the more mental activity the BCI touches. In 2018, the measurement precision of BCIs first reached the level of the sub-microvolt in amplitude [7]—that is, 0.5 μV—which significantly broadened the category of BCIs.

1. Challenges

Although tremendous progress has been made in BCI research in recent years, it remains challenging to make the leap from the lab to the marketplace. BCIs are a multidisciplinary subject involving many research fields, including neuroscience, computer science, materials, electronics, ergonomics, and mechanical engineering. Therefore, concerted efforts must be made by researchers in different fields to fulfill the practical application of BCIs. Here, we highlight two formidable challenges that require more attention from the BCI community.

(1) **The current manner of wearing a BCI reduces its range of application.** To date, nearly all EEG-based BCI systems consist of electrodes, an amplifier, and some accessories, such as a cap. Therefore, such a system's shape and manner of wearing directly determine the potential application scenarios of the BCI. To acquire high-quality EEG, most studies are conducted using high-precision, multi-channel EEG instruments that are, however, too bulky and heavy to be wearable. As a result, these instruments can only be used in scientific research and medical applications. To solve this problem, portable EEG products have been developed that are much smaller and lighter, and can be mounted onto the head [8]. However, a cap or something similar is still necessary for the portable EEG instrument to host electrodes. For some products, a headband is used to secure the electrodes, making them more compact and easier to wear. Even so, it is still very difficult to persuade normal, healthy people to wear an uncomfortable and ugly EEG cap or headband in everyday life, because current BCI systems have limited capacity and cannot provide healthy people with a vital function for improving their lives. Actually, in most cases,

https://doi.org/10.1016/j.eng.2021.09.011

the benefits offered by BCIs are insignificant or even unclear in regard to the performance of our duties. Therefore, wearing an EEG cap/headband or BCI is not fully justified or motivated for healthy individuals, compared with motivated patients who want to use BCIs to replace, repair, enhance, supplement, or improve the normal output of the brain. Therefore, increasing the accessibility of BCIs is an essential step forward in incorporating the most direct form of human–machine communication into everyday life; it would also provide valuable insight into the workings of the healthy brain

(2) **Unnatural brain–computer (BC) interaction in a BCI hinders the BCI's usefulness.** Over the past 50 years, the BCI community has put most of its effort into increasing the ITR between the brain and the computer, while neglecting the user-friendliness of the interaction between them. Therefore, the BCI paradigm is seriously underdeveloped, and current BCI studies can almost be said to be based on paradigms invented about 30 years ago, such as motor imagery [9], P300-speller [10], and steady-state visual evoked potential (SSVEP) [4,5,11]. These traditional BCI paradigms have been successfully demonstrated by transmitting information from the brain to a computer. Nevertheless, they are unnatural for the brain to interact with and thus require many more cognitive resources to perform an action than traditional human–computer interfaces. For example, the SSVEP-BCI is currently the most efficient BCI system in terms of ITR. It can produce a command in about 1 s [4,5]. However, to obtain a high-quality SSVEP, the flickers used to encode the BCI command must be sufficiently large and intense, which will engage a relatively large portion of the visual resources. Moreover, such irritating visual stimuli are not only irrelevant to users' subjective intent, but even disrupt users and make them feel uncomfortable. Therefore, even though this BCI system can work well in certain scenarios, its unnatural way of interaction is unacceptable to users, which reduces its usefulness in practice.

2. Future research directions

Immediate action must be taken to tackle these two urgent challenges, which we believe to be the main barriers to the practical application of BCIs at this stage. As both are complex problems that are impossible to solve within a single discipline, collaborative work is needed to gather the wisdom of researchers with different specialized knowledge. Here, we summarize several important research topics that are expected to overcome these challenges. We hope these topics will lead to valuable discussions and studies in the BCI community.

(1) **New metrics for evaluating BC interaction.** In previous studies, BCI performance has typically been assessed by means of classification accuracy and ITR. However, both metrics focus only on assessing the transfer of information for the BCI; they are not appropriate for assessing the efficiency of BC interaction in a real and complex human–computer interaction scenario, which should consider the human factor in a closed-loop operation [12]. Therefore, from a practical perspective, new metrics should be proposed to measure the overall performance of a BCI system, such as the brain-to-hands ratio (BHR) [13]. The BHR is computed by dividing the performance score achieved using the BCI by that achieved using hands, for the same task by the same person.

(2) **Innovations in BCI hardware to make it more user-friendly.** As mentioned above, the current BCI hardware is unacceptable to most healthy people. Therefore, innovations in EEG electrodes, circuits, ways of assembly, mounting mechanisms, and wearing methods are urgently needed to make the BCI hardware more compact, comfortable, and easy to use. For example, a small EEG recording device that can be invisibly hidden underneath the hair would be more popular than the current cumbersome models.

(3) **BCI paradigms with a low cognitive load.** Traditional BCI paradigms often cost users many cognitive resources, making the BC interaction unnatural and "stagy." Therefore, we strongly suggest that researchers move from those traditional BCI paradigms to developing new BCI paradigms that can significantly reduce the cognitive load of the user.

(4) **BCI algorithms guided by EEG mechanisms and characteristics.** The BCI algorithm is the key link to decoding the brain's intention. In the domain of image and speech recognition, the object to be recognized can be clearly identified by humans. As a result, researchers can use their experience and inference to guide the extraction of features and the construction of classifiers. However, raw EEG signals are rather incomprehensible to humans. Thus, we will be blind in developing BCI algorithms if we have no idea how an EEG unfolds or what features it contains. Therefore, a thorough understanding of EEG mechanisms will greatly help and guide the design of BCI algorithms [7]—although such an understanding has been ignored in most previous studies. Furthermore, the pervasive and elusive EEG variability among different individuals, as well as within a single individual across time, limits the reproducibility of specific brain responses used in BCIs and thus reduces the generalizability of brain-decoding algorithms [14–16]. Advanced BCI algorithms need to mitigate intra- and inter-subject variability in order to create a robust BCI. To understand the neural mechanisms behind such EEG variability is a promising approach that will aid in solving this problem.

In sum, BCI development has entered the stage of studying BC interaction. Therefore, all questions concerning the natural interaction between the brain and the computer—including but not limited to the four crucial topics mentioned above—should be studied in depth in the future.

Acknowledgments

We appreciate the financial support from the National Key Research and Development Program of China (2017YFB1300300); the National Natural Science Foundation of China (62122059, 81925020, 61976152, and 81630051); and the Young Elite Scientist Sponsorship Program by CAST (2018QNRC001).

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