ISSN 2959-409X

Enhancing Decision-making Function Using Brain-computer Interface

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Abstract:

Brain-computer interfaces (BCIs) are one of the key research topics today, particularly important in the field of neuroscience, and researchers have found that BCIs can be applied not only to stroke or paralyzed patients to allow them to manipulate external devices through brain activity but also to the more abstract field of decision making. Currently, brain-computer interfaces are helpful in decision-making, mainly by improving various algorithms or applying strategies to improve the correctness of decisions. This would certainly help to address the uncertainties or major mistakes that occur when people are faced with the choices they make in their daily lives. However, there is a lack of a systematic understanding of the mechanisms behind them and the advantages and disadvantages of various approaches. The main focus of this review is to introduce the basic workflow of BCIs as well as several approaches that have been used in recent years to help improve decision-making (e.g., meta-learning approaches based on transfer learning, collaborative brain-computer interfaces, etc.). The aim is to understand the mechanisms behind them and their advantages and disadvantages. On this basis, a few suggestions are made in order to identify potential possibilities for further research.

Keywords: Brain-computer interface (BCI); prefrontal cortex; decision-making

1. Introduction

In daily life, people always encounter a variety of choices. For example, when there is coffee, tea, and ordinary water in front of you, you will be confused about which one to choose; when you want to purchase a house or a car, you will take into account a number of factors and thus choose a more appropriate one. Such people need to make a definite choice based on a combination of contextual cues and prior knowledge to achieve a specific goal; this process we can call decision-making [1].

Decision-making is ubiquitous, and there are many factors that influence decision-making, such as the value of the options faced and the consequences of the choices made (personal, other people‘s, social). In general, for organisms, the motives for making decisions tend to be to avoid harm. According to previous findings, one of the main brain regions that influence decision-making is the prefrontal cortex (PFC), and its different subregions, in turn, influence different aspects of decision-making. For example, some researchers conducting experiments on economic decision-making in rats have found that the orbitofrontal cortex (OFC) in the prefrontal lobe plays an important role [2]. In addition, this region is also thought to be involved in value-based deliberate decision-making, with neurons that encode the value of the selected option [3]. There are times when more than a few choices are faced, such as when faced with multiple choices, and the dorsolateral prefrontal cortex (dlPFC) is crucial in filtering out information that is irrelevant to decision-making [4]. In addition, neuroscientists find that the ventral medial prefrontal cortex (vmPFC) is generally engaged in various decisions. Still, when faced with more complex environmental decisions, the lateral prefrontal cortex (PFI) may be more important [5]. Decision-making is a complex process, however, and different subregions of the prefrontal cortex often interconnect with other regions to form neural circuits that guide decisions. For example, when an organism (primate or human) chooses a favorable outcome for itself, there exists a valuation circuit that includes the vmPFC, OFC, anterior cingulate cortex (ACC), ventral striatum, and the amygdala, among others, which are active in the processes involved in the valuation decision, and which would also be active in response to different forms of reward and punishment [6].

There is a vast body of research on decision-making, which we will not go into here. In contrast, people may be more concerned with making choices in their lives that are more favorable to themselves, especially in the face of a complex environment where time is of the essence, ensuring that their choices are not wrong, assisting people in making choices, and so on. The advent of brain-computer interfaces seems to open up more possibilities for these issues as neurotechnology advances. The field of brain-computer interfaces (BCI) encompasses neuroscience, signal processing biomedical sensors, and other disciplines. Brain-computer interface systems can directly link the human brain to the external environment, allowing users to manipulate devices through brain activity signals rather than nerves or muscles [7]. Traditionally, BCIs are commonly used to help injured or impaired patients recover, e.g., by helping patients control devices such as prosthetic limbs and wheelchairs [8]. As human needs increase, it is also used for memory enhancement, error detection, trust assessment, and group decision-making [9]. In this paper, the author will discuss how BCIs can be utilized in the PFC, in what ways they can help decision-making, and the neural mechanisms behind them, with the aim of helping human beings live better lives and discover potential possibilities.

2. Related Works

2.1 BCI Basic Process

Before we start with the formal content, it is necessary to understand some of the basics of BCIs in order to understand how BCIs can improve the correctness of decision-making. The concept of BCIs has been proposed since the last century through continuous research and development of predecessors, gradually moving from theory into reality and ultimately being applied in a number of fields. According to M.F. Mridha et al [7], the workflow of a BCIs can be roughly characterized as signal acquisition, pre-processing, feature extraction, classification, controlling the device, and finally feedback evaluation. These processes described above and the principal methods involved therein are illustrated in Figure 1, and the particulars will be set forth below. Experts and scholars in the field may delineate roughly the same stages, but that doesn‘t prevent us from understanding how it works.

BCIs work mainly based on the signals from brain activity, which can be categorized into different types, the more common ones being visual steady-state evoked potentials (SSVEP), which are derived from periodic stimuli experienced by the subject (e.g., flickering images, modulated sounds, or vibrations), and P300 evoked potentials, which are produced from infrequent visual, auditory, or somatosensory inputs to the electroencephalogram (EEG) peak potentials, which require the user to make a response to a series of random stimuli and also tend to cause user fatigue. The acquired signal may not be directly usable and is filled with noise caused by various factors, in which case it needs to be preprocessed, or as some call it, signal enhancement. Commonly used methods include independent component analysis (ICA), common average reference (CAR), and signal denoising, etc. where signal denoising can eliminate sounds or artifacts in the EEG signal.

Then, feature extraction work needs to be done on the processed signal as a way to reduce the workload and improve efficiency. The EEG-based BCIs is often performed the process of feature extraction via three directions: time domain, frequency domain, and time-frequency domain. In the end, the extracted features should be classified in order to send commands to external devices. As the neural technology develops, a growing number of BCIs are now using neural networks as classifiers, among which convolutional neural networks (CNN) are mainly used for image analysis and recognition and visual input processing, including convolutional, pooling, and fully-connected layer structures. Currently, the choice of classifiers for BCI may not be limited to a single one but rather a combination of tools to improve efficiency. BCI needs to be adjusted using algorithms or user feedback.

Some scholars categorize brain-computer interfaces according to different classification criteria [7, 10, 11], which can be broadly classified as invasive and non-invasive. Invasive brain-computer interfaces with clear signals can directly monitor the activity of each neuron. Still, they are subject to foreign body reactions and post-surgical scarring and are currently only suitable for patients with moderate to severe paralysis, for example. There are also semi-invasive BCIs, such as cortical electroencephalography (ECoG), as well as non-invasive BCIs including electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (FMRI), and functional near-infrared spectroscopy (FNIRS), etc., which are used in a wide variety of fields with the advantages of low cost and portability. Interestingly, Gao et al. further elaborated the brain-computer interface (BCI) from an evolutionary perspective, including the classical brain-computer interface era, the brain-computer interaction era, and the currently developing brain-computer intelligence era [12].

2.2 Applications of BCI in Improving Decision-Making

Brain-computer interfaces seem to be able to combine with various fields and have unlimited possibilities, no longer limited to the traditional forms. Since humans make choices almost all the time in their daily lives, they combine the information they already have with various conditions to synthesize and ultimately form a decision and execute it. If there is a way to help humans make better decisions, it will bring a lot of benefits. Current research on brain-computer interfaces to improve decision-making mainly focuses on improving some of the corresponding algorithms or decision-making, which in turn improves the accuracy of decision-making. Some researchers believe that the metacognitive evaluation of decision-making, i.e., confidence, can, to a certain extent, respond to the accuracy of decision-making. This measure is also considered to be similar to other physiological measures, such as reaction time (RT) status [1, 13]. Some researchers have also argued that recent machine learning-based decision decoders and brain-computer interfaces for improving decision correctness have also gradually utilized neural representations of decision and confidence [14].

Christoph Tremmel et al. proposed that meta-learning based on transfer learning techniques can improve the performance of BCI in decision confidence prediction [13]. Based on the previous common practice of predicting decision confidence through EEG, which has certain drawbacks such as inaccurate prediction and the possibility of leading to domain bias problems, since modern BCIs are in accordance with machine learning algorithms, there may be a mismatch among the training algorithm and the new data, which indirectly increases the time of training the user prior to the use of the BCI, and to some extent, may also lead to the generalization of BCIs. For this, they adapted meta-learning by means of a biased regularization algorithm, a method that generates predictive algorithms from the data of previous testers and then quickly adapts the algorithms to the new participants‘ situations. (By comparing the meta-learning approach to several other methods, including the traditional BCI single-subject training method, domain-adversarial neural networks, and the transfer learning method of zero-task-like training), they found that the meta-learning approach was superior, as shown in Table 1.

In addition, SuJin Bak et al. proposed a BCI-based brain signal processing method to measure behavior when people make decisions such as impulsive spending, aiming to reduce ambiguity and guesswork in the data. This study utilized functional near-infrared (fNIRS) to detect impulsive consumption behavior and observe prefrontal cortex activation, providing evidence of a potential biomarker that could provide new possibilities for the development of BCI [15].

When faced with important decisions, such as the introduction of a policy, the enactment of laws, etc., it is basically a specialized committee (think of it as a large team) that votes or uses other methods of decision-making to reduce the risk of avoiding devastating catastrophes due to the false sense of confidence of an individual. Davide Valeriani et al. present a new perspective on how BCI can improve human decision-making. How BCI can improve human decision-making: Their team has proposed a multimodal BCI to help humans make big decisions in a larger environment [14]. They used EEG or fMRI to isolate relevant neural markers (confidence, etc.) and then allowed machine learning to decode these neural marker features to augment the BCI‘s team decision-making. (By comparing the performance of different-sized teams with standard majority decision-making or weighted individual decision-making) they showed that BCI-assisted team decision-making accuracy is superior (because BCI is able to capture the unique neural correlates of confidence). In addition, during their experiments, they found that the neural markers of decision accuracy used were in the SPL and visual cortex, relying on parietal-occipital and δ rhythms, and frontal-temporal β rhythms. In contrast, the markers of subjective confidence were not only in the SPL, but also extended to areas such as the middle prefrontal and basal ganglia, which could suggest that our next BCI studies might focus on areas such as the prefrontal and basal ganglia. On prefrontal and other regions to explore further neural mechanisms.

Not coincidentally, Saugat Bhattacharyya et al. introduced collaborative brain-computer interfaces (cBCIs) and tested them in two military scenarios (patrol experiment and outpost experiment) and found that the interfaces significantly improved the efficiency of group-perceived decision-making [8]. This collaborative biometric identification (cBCIs) can integrate the brain activity of multiple users to complete the goal; they developed a hybrid cBCI combining the use of neurological, behavioral, and physiological measures to evaluate the objective confidence of the users one by one and then finally aggregating the contribution of each individual and using his/her confidence as a decision weighting to form the final result of the group decision.

Alireza Rouzitalab et al. suggest that the brain processes relatively limited information in order to make the most appropriate choices. The pathway seems to be that sensory information reaches the posterior parietal cortex (PPC), which subsequently transfers the signal to the PFC and premotor cortex (PMC), and the processed information is then sent to the primary motor cortex (M1) for a response [16]. Unfortunately, however, little has been seen so far on the neural mechanisms by which the interbrain interface actually acts on the prefrontal cortex to modulate and thus influence decision-making. An approximate brain-computer interface working mind map is shown in Figure 1.

3. Discussion

Several BCI approaches mentioned in this article to help improve decision-making include meta-learning (new transfer learning methods), collaborative brain-computer interfaces, brain-computer interfaces, and methods that utilize functional near-infrared (NIR) detection and analysis to improve the accuracy of various forms of decision-making by improving the BCI's workflow (e.g., by proposing or refining new algorithms or strategies or by searching for potential neural markers of subjective sensations, etc.). To some extent, their methods can complement the shortcomings of existing algorithms or research strategies and provide new reference directions. However, the target objects compared in the above studies seem to be a bit limited, and further comparisons with existing mainstream methods are needed. In addition, the above study was only conducted in a small number of healthy people. It did not take into account the existence of other populations in the social structure (e.g., people with disabilities, people with mental disorders, people with atresia syndrome, and healthy people working in various professions etc.) The scope of the experiments needs to be further expanded to validate the results.

According to Gangopadhyay P et al. [17], they have broadly categorized decision-making in rodents, primates, and humans regarding social dimensions into three phases (social cognition; social learning, evaluation, and reward; and social action or response), and they explored each of their three phases, elaborating on the role that the prefrontal cortex (PFC) (including its various subregions)-amygdala neural circuit plays a role in decision making.

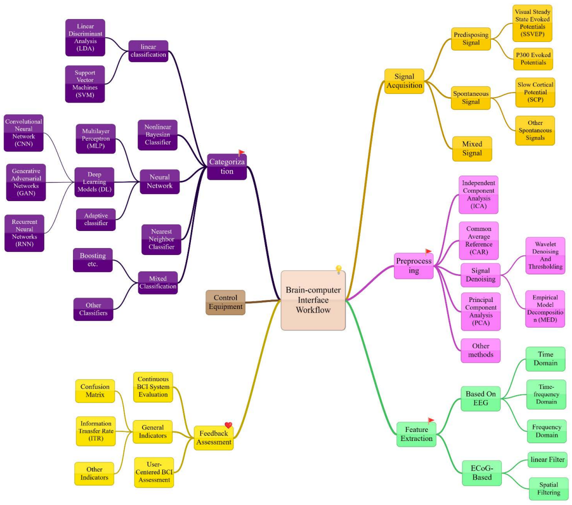

Fig. 1 Approximate brain-computer interface working mind map (Photo credit: Original)

Table 1. Summary of relevant research on brain-computer interfaces to help improve decision-making.

Strategies	ADVANTAGES	brief introduction
Transfer learning techniques according to meta-learning[13]	lSequential processing of data (e.g., using source and target data) and no need to keep the training set in memory (low memory footprint as well as low complexity) lIntegrates the advantages of mainstream single-subject methods with the versatility of multi-subject methods without adding to their disadvantages lImprove performance with less data lVarying degrees of participant performance improvement lMeta-learning algorithms improve incrementally with more and more available source data lMeta-learning produces confidence predictions that better regulate the correctness of decisions	Meta-learning is based on two previous phases of meta-training (iteratively training BCIs with prior participant data to obtain domain-invariant features) And fine-tuning (fast fine-tuning of BCI with data from new participants). A validation fine-tuning step has also been added.
Multimodal collaborative brain-computer interfaces[14]	lEstimate the possibility of a correct decision from neural signals, thereby notably improving the accuracy of the team's decision-making in identifying hazardous areas. lImprove decision-making in pandemic scenarios.	Separate decision-related neural markers of confidence and trust by EEG/functional magnetic resonance imaging (EEG/fMRI) and let machine learning decode these neural markers to enhance team decision-making correctness.

Collaborative Brain-Computer Interfaces (cBCIs)[8]	lMake roughly reliable decisions, and the longer you wait, the better the results will be lCan meet the challenges of time progress and decision-making complexity	It combines behavioral, physiological, and neurological data and utilizes event-related potentials (ERPs) that are triggered by brain activity. When a potential threat is present, provides collective decision-making at any time after team members have voted.
Functional near-infrared (fNIRS) based brain-computer interfaces[15]	lReducing bias initiated by conscious thought is evaluated through self-reports and ensures the ecological validity of people's behavior as well. lThe emergence of biomarkers for fNIRS increases the potential for impulsive buying detection and can improve the prediction of human buying decisions.	Detection of prefrontal activation during impulse consumption by functional near-infrared (fNIRS) provides potential biomarkers.

Moreover, in a study by Zoh Y, et al. [6], it was also mentioned that the brain regions designed for these decision-related activities, including motivation, representation, valuation to action selection, were found to include vmPFC, OFC, ACC as well as the ventral striatum and amygdala in a study on primates and humans. These findings seem to suggest that decision-making is a very complex process and that the generation of a decision is not confined to a single but multiple brain regions acting to form potential neural loops, which may be particularly important for future research. It seems that brain-computer interfaces can improve decision-making not only by improving algorithms or applying strategies to improve decision-making accuracy but also by intervening in a particular brain region or neural circuit to assist in decision-making.

Based on Collins AGE et al.'s study [18], it seems that it can shed light on the next BCI research on decision-making directions, such as considering the influence of multiple systems on each other and exploring the situation where an individual decides with respect to the judgmental valuation of the outcome (i.e., a person may consider whether or not this should be done, and what the outcome will be if it is done, either through intrinsic or extrinsic factors), and so on. In addition, Liu Y et al. also studied the research on environmental control of human and rehabilitation hospitals [19], which also provides potential possibilities for the next brain-computer interface; imagine when the user is in the external environment to see a certain object in mind flashed a certain idea, there will be a list of options will be popped up in front of the eyes, and only the brain's ideas can be made to make a choice (the user to do certain actions or the selected object to make some kind of change to fit the user's ideas), which will greatly improve the efficiency of life. Indeed, studies with primates and rodents are not unique. Although their decision-making styles and associated brain regions are different from those of humans, they can provide general ideas for subsequent research. Balewski ZZ et al. [3] studied decision-making in rodents and primates, and this may provide insights, but of course, obedience takes a lot of time to train, and the associated mental representations are not directly available, making it difficult to validate the results another great challenge. Training and the fact that relevant mental representations are not directly available to validate the results is another great challenge. In addition, physiological processes related to decision-making may be regulated by a variety of substances, such as the neuropeptide oxytocin (OT) [17]. Suppose future brain-computer interfaces are able to decode the release of related hormones or the choice of the pathway of action. In that case, they may also indirectly play a role in decision-making.

4. Conclusion

This article introduces the basics of the workflow of brain-computer interfaces (BCIs). It describes some of the research on the role of BCIs in decision-making, with the aim of helping readers understand the ways in which BCIs can intervene today (either through BCIs' algorithmic improvements or through the joint use of multiple applications for decision-making, etc.) to assist human decision making (by improving confidence in decision making and thus increasing the rate of decision making correctness). Although this article does not go further to compare the effects of the various approaches horizontally, probably due to the fact that there are too many differences in the studies to be directly comparable, and there is no data available to validate or further explore the mechanisms of BCIs for improving decision making. However, some potential research directions of brain-computer interfaces on decision-making (e.g., the influence of multiple systems in brain regions on each other or some new kind of bioinformation decoding, as well as possible human-environment interaction decision-making, etc.) can be identified through this paper with the aim to better carry out the subsequent research.

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