Low-quality training data detection method of EEG signals for motor imagery BCI system

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ABSTRACT

Background: The design and implementation of high-performance motor imagery-based brain computer interface (MI-BCI) requires high-quality training samples. However, fluctuation in subjects’ physiological and mental states as well as artifacts can produce the low-quality motor imagery electroencephalogram (EEG) signal, which will damage the performance of MI-BCI system.

New method: In order to select high-quality MI-EEG training data, this paper proposes a low-quality training data detection method combining independent component analysis (ICA) and weak classifier cluster. We also design and implement a new online BCI system based on motor imagery to verify the online processing performance of the proposed method.

Result: In order to verify the effectiveness of the proposed method, we conducted offline experiments on the public dataset called BCI Competition IV Data Set 2b. Furthermore, in order to verify the processing performance of the online system, we designed 60 groups of online experiments on 12 subjects. The online experimental results show that the twelve subjects can complete the system task efficiently (the best experiment is 135.6 s with 9 trials of subject S1).

Conclusion: This paper demonstrated that the proposed low-quality training data detection method can effectively screen out low-quality training samples, so as to improve the performance of the MI-BCI system.

1. Introduction

Brain-computer interface (BCI) technology provides a communication link between the brain and the external world by translating brain activity signals into machine language. It has the potential for a wide range of applications in our daily life and has received extensive attention from researchers in recent years (Mane et al., 2020; Gaur et al., 2021; Arpaia et al., 2021; Ravi et al., 2022; Anbarasan et al., 2022; Ma et al., 2022). Motor imagery-based brain computer interface (MI-BCI) is an implementation mode of endogenous EEG-BCI, which is driven by amplitude modulation of mu/beta rhythm when the user performs motor imagery. This phenomenon is known as event-related synchronization/desynchronization (ERS/ERD) (Ramoser and Muller-Gerking, 2000). Compared with exogenous BCI systems, such as SSVEP-based BCI, the advantage of MI-BCI is that users can control external device through their own mental activity (motor imagery) without the help of external stimuli.

The MI-BCI system usually consists of preprocessing, feature enhancement and acquisition, classifier and control command generation modules. Among them, the spatial filtering technology based on multi-channel EEG signals plays a very key role in the design of MI-BCI system (McFarland et al., 1997). A spatial filter with excellent performance can significantly improve the signal-to-noise ratio (SNR) of the multi-channel EEG, thereby providing accurate EEG features for subsequent classifier learning and MI type recognition. Therefore, the performance of the spatial filter largely determines the overall performance of the MI-BCI system (Sakashita et al., 2007). At present, the commonly used spatial filtering methods include common spatial pattern (CSP) (Gubert et al., 2020; Zhang et al., 2017; Saha et al., 2020; Gaur et al., 2021; Goupilpailler et al., 2010) and independent component analysis

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(ICA) (Zheng et al., 2019; Maddirala and Shaik, 2017; Wu et al., 2020; Fedosov et al., 2020; Safitri et al., 2020), which need to be designed by using the MI-EEG training data collected in advance. Therefore, its performance is closely related to the quality of the training data.

In the past few decades, researchers have carried out extensive and in-depth research on MI-BCI system implementation. During the period, many improved spatial filtering algorithms (Lotte and Guan, 2011; Wu et al., 2015; Zhang et al., 2007; Feng et al., 2018; Chen et al., 2017b; Ang et al., 2012) and new machine learning methods, such as deep learning, etc., are introduced (Dose et al., 2018; Craik et al., 2019; Schirrmeister et al., 2017), but the stability and generalization performance of the MI-BCI system is still far from the actual requirements (Jayaram and Barachanti, 2018; Jayaram et al., 2018). On the one hand, the reason may be that the MI-EEG training data are limited, which makes the MI-BCI model not fully learned and trained; on the other hand, it may be inevitable that the low-quality training data will reduce the migration performance of the MI-BCI system. Because the MI-EEG collection experiment is limited by many objective conditions, it is not easy to obtain a large number of high-quality training data. Therefore, it should be a feasible research idea to use the existing MI-EEG dataset to improve the performance of the MI-BCI system from the quality assessment and optimization of training data.

Generally, the MI-EEG training set consists of several single trials with MI labels. The main factors affecting the quality of the single trial includes: (i) Artifact interference: such as spontaneous EEG, electrooculogram (EOG), electrocardiogram (ECG), electromyogram (EMG) and other physiological artifacts, power-line interference, and the connection failure between electrode and scalp, etc. Low-quality training data containing strong interference artifacts will have unpredictable effects on the design of the spatial filter and classifier; (ii) The mental state of the subject fluctuates: The collection time of MI-EEG training data is generally relatively long. However, too long a period of time will cause the subject to fail some single trials due to fatigue or lack of concentration. For example, the subject did not perform motor imagery accurately. For MI-EEG training data collected in advance, therefore, its contribution of the source, $I(s_j)$ is the joint entropy of $s_j$, $I(y_j)$ denotes a mixing coefficient of the $j$-th source. $x$ is the $N$-channels EEG signals. $A$ is an $N \times N$ mixing matrix and $a_j$ the $j$-th column vector of $A$, which reflects the projection coefficient of the $j$-th independent source $s_j$ in each channel EEG signal.

The inverse form of Eq. (1) is called the separation model, namely:

$$y = Wx$$

where $y = [y_1 \cdots y_N]^T$ is the observation vector, $W$ is the mixing matrix, and $x = [x_1 \cdots x_N]^T$ is the source vector. $W$ and $x$ are both $N \times N$. The goal is to find the inverse mixing matrix $W^{-1}$ to obtain the source signals $x$ from the observed signals $y$. $W^{-1}$ can be obtained by maximizing the mutual information of the source and the observed signal.

$$W = \arg \max_w \{I(f(y))\}$$

where $f$ is the nonlinear function related to the probability distribution of the source, $H(f(y))$ is the joint entropy of $f(y)$, $I$ is the mutual information, and $\text{sign}(\cdot)$ denotes the sign function.

To summarize, the main contributions of this paper are as follows:

- Firstly, a low-quality data detection method is proposed to screen low-quality training samples caused by different factors.
- Secondly, we study the possibility of reusing low-quality samples.
- Finally, an online asynchronous MI-BCI system is designed and implemented.

The rest of this paper is organized as follows: Methods are discussed in Section 2. Section 3 describes the proposed online asynchronous MI-BCI system. The experimental results are presented in Section 4. Section 5 draws conclusions.

2. Methods

In this paper, we propose the low-quality data detection method to screen low-quality training samples. In addition, we introduce the ICA spatial filter and the blink detection method based on dual-threshold.

2.1. ICA spatial filter

The ICA spatial filter is derived from the linear mixing model of multi-channel EEG signals (Parra et al., 2005), as shown in Eq. (1).

$$y = Wx$$

where $y$ is the estimation of the independent source $s_j$, $W_j = [w_{j1} \cdots w_{jN}]^T$ is the $j$-th row of $W$, that is, the $j$-th spatial filter.

ICA is a kind of blind source separation (BSS) technique based on the statistical independence of sources. So far, researchers have proposed various ICA/BSS algorithms, such as Infomax, FastICA, Jade, and SoB (Lee et al., 1999; Hyvarinen and Oja, 2000; Comon, 1994; Belouchrani et al., 1997; etc. In this paper, a simplified Infomax algorithm is adopted, as shown in Eqs. (3) and (4). The algorithm takes the information maximum criterion as the independence measurement and adopts the natural gradient algorithm to calculate the separating matrix $W$ (Comon, 1994).

$$W = \arg \max_w \{H(f(y))\}$$

$\Delta W = (I - E[yy^T + \text{sign}(yy^T)])W$
2.2. Low-quality training data detection method

It is inevitable that low quality data exist in the process of MI-BCI system design and training. They will have varying degrees of negative impact on the performance of the built BCI system. In this paper, with the help of the idea of ensemble learning (Zhuang et al., 2019), we propose a novel low-quality training data detection method to evaluate the data quality of a single trial and screen out the low-quality single trial in the training data.

2.2.1. Single-trial-based classifier: STC

Let \( x_j, j = 1, \ldots, L \) be a single trial in training set \( D \). The ICA spatial filter is designed by using a single-trial \( x_j \) and the corresponding MI classifier denoted by \( STC(j) \) is constructed. Fig. 1 shows the structure of STC, which consists of modules of ICA calculation, spatial filtering, classification and two bandpass filters (BPF1 and BPF2). BPF1 usually has a relatively wide bandwidth (such as 8–30 Hz or 5–35 Hz), which is conducive to ICA calculation. In order to further improve the signal-to-noise ratio of motor-related independent components (MRICs), the bandwidth of BPF2 is set for the specific frequency band of ERS/ERD of each subject, so the bandwidth of BPF2 is usually narrower than that of BPF1. The classification rule adopted in STC is defined based on the variance comparison of MRICs.

In STC, ICA is applied to each trial \( x_j \) that contains \( N \)-channel MI-EEG signals with duration \( t_c \) (see Fig. 6), and the separating matrix \( W_j \) and the mixing matrix \( A_j \) are obtained. Then, the columns of \( A_j \), i.e. spatial patterns of independent components (ICs), are employed to determine the MRICs, and the row vectors of \( W_j \) corresponding to the achieved MRICs are selected as the spatial filters, named \( w_1 \) and \( w_2 \) in two-class MI tasks. Thus, for the training set \( D \) with \( L \) single trials, the \( L \) STCs: \( STC(j) \) for \( j = 1, 2, \ldots, L \) could be obtained; each of them is applied back to test the trials in training set \( D \), and \( L \) classification accuracies could be achieved, denoted by \( Ac(j) \). As previously mentioned, the performance of ICA spatial filters are very sensitive to some types of artifacts in EEG data, so the accuracy \( Ac(j) \) achieved by \( STC(j) \) can indicate whether the single trial \( x_j \) for ICA calculation is heavily contaminated.

2.2.2. Low-quality trial detection based on STC

With a set of STCs, an algorithm of low-quality trial detection for the training set can be established, which is described as follows:

- The softmax algorithm described in Eq. (4) is applied to the single trial \( x_j \) in training set \( D \) and the corresponding \( STC(j), j = 1, 2, \ldots, L \) are constructed.

- Each training trial \( x_i, i = 1, 2, \ldots, L \) is classified by \( STC(j), j = 1, 2, \ldots, L \), respectively. The recognition matrix \( C = \{C(j, i), i = 1, \ldots, L \} \) is obtained. The element of \( C \) is “0” or “1”, indicating that \( x_i \) is correctly classified or misclassified by \( STC(j) \) (see Fig. 2).

- The projections along the horizontal and vertical directions respectively are obtained from the matrix \( C \), as shown in Eqs. (5) and (6).

\[
Q_h(i) = \frac{\sum_{j=1}^{L} C(j, i)}{L}, \quad i = 1, \ldots, L \tag{5}
\]

\[
Q_v(i) = \frac{\sum_{j=1}^{L} C(i, j)}{L}, \quad i = 1, \ldots, L \tag{6}
\]

The classification accuracy \( Ac(j) \) is calculated as follows:

\[
Ac(j) = \left( 1 - \frac{\sum_{i=1}^{L} C(i, j)}{L} \right) \times 100\% \tag{7}
\]

As can be seen from Fig. 2, the recognition matrix \( C \) is practical for the selection of low-quality training set data. The elements in \( j \)-th row of the matrix \( C \) corresponds to the recognition results to all training trials achieved by \( STC(j) \). Obviously, the more “1”s in the \( j \)-th row, the greater the \( Q_v(j) \) value, indicating that the classification performance of \( STC(j) \) is relatively poor, and furthermore the single trial \( x_j \) used for \( STC(j) \) design may be heavily corrupted by artifacts. The \( i \)-th column of the matrix \( C \) represents the recognition results of \( L \) classifiers \( \{STC(i), j = 1, \ldots, L \} \) applied to the single trial \( x_i \). The larger \( Q_v(i) \) value means more “1”s in the \( i \)-th column of the matrix \( C \), implying that the single trial \( x_i \) is misclassified by most STCs, so \( x_i \) may be a mislabeled trial.

According to the analysis of the reasons affecting MI EEG data quality in this paper, the low-quality single trial in the training data can
be divided into three categories, namely: (i) the trials with strong artifactual interference; (ii) the trials with extremely weak ERS/ERD effect; (iii) the trials with clear ERS/ERD effect but mislabeled. Obviously, the first two categories of the low-quality trials can be eliminated, while the third category can be reused through relabeling. In the low-quality data detection method proposed in this paper, \( Q_h \) can be used to detect the first category of low-quality trials, and \( Q_v \) value is used to detect the last two categories of low-quality trials.

2.3. Blink detection method

Because the energy of EOG signal will increase significantly during blinking, and the energy will decrease significantly at the end of blinking. Therefore, we adopt the dual-threshold method with low temporal and spatial complexity to detect blinking movement. We set a high threshold \( E_H \) to detect the blink signal amplitude rise state, and set a low threshold \( E_L \) to detect the fall of the amplitude. When the amplitude of the EOG signal is first higher than \( E_H \) and then below \( E_L \), the blinking is considered to be once (as shown in Fig. 3).

3. An online asynchronous MI-BCI system

In this paper, we design an online asynchronous BCI system based on motor imagery. The hardware platform of the system consists of neuroscan multi-channel EEG acquisition amplifier and PC. It includes stimulation computer running stimulation software (STIM), acquisition computer running acquisition server software (SCAN) and two client running MI-BCI system and simulation control System (SCS) respectively. MI-BCI is the core system of this platform. The online system consists of following modules: signal acquisition and preprocessing, low-quality training data detection, ICA spatial filter design, two-blinks detection, classification and finally, GUI control. These modules are presented in Fig. 7.

3.1. Signal acquisition and preprocessing module

During signal acquisition, each subject is asked to sit in a comfortable armchair, facing a computer screen displaying the visual cue. And they are given instructions to stay fully relaxed without body movements to avoid motion artifacts. The signal acquisition equipment comes from American NeuroScan company, including multi-channel EEG amplifier, electrode cap, acquisition software and connectors. EEG data are recorded from 16 scalp electrodes (VEOU, VEOL, FP1, FP2, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, O1, Oz, O2) placed at locations according to the standard international 10–20 system (Fig. 4) with the left mastoid served as the reference (electrode: R) and the right mastoid as the ground (electrode: G). However, there are two different electrode-distributions that can be used as BCI inputs for different subjects, one is an eight-channel scheme (FP1, FP2, C3, Cz, C4, O1, Oz, O2) and the other is a nine-channel scheme (FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4). The electrode of VEOU is fixed above the right brow to detect eye-blinking movement (Fig. 5). Previous studies have shown that the use of too many electrodes does not help to improve the overall recognition performance of ICA filtering and BCI system. The experimental paradigm for a single trial is depicted in Fig. 6. In general, a single trial consists of a blink detection period (duration \( t_b \)), motor imagery period (duration \( t_s \)), and a rest period (duration \( t_r-t_s \)). It is worth mentioning that in order to realize the asynchronous control of BCI system, we use two-blinks as the “switch” in the motor imagery period. The success of subjects’ autonomous two-blinks detection indicates the beginning of a motor imagery period. And then a cue of MI class is presented at the center of the monitor and lasts for \( t_s \) seconds. Within this period, the subjects can perform the desired motor imagery task. Then, a short break (relaxation period) follows lasting for \( t_r-t_s \) seconds, and the subjects relax and is ready for the next two-blinks (the beginning of next trial). The raw EEG signals are band-pass filtered between 0.1 and 100 Hz, and digitally sampled at 250 Hz. An additional 50 Hz notch filter is applied to suppress the power line interference (Fig. 7).

3.2. Low-quality training data detection module

In the design of MI-BCI system, the EEG segment with a duration of 100 s is collected as the training data, the low-quality training data detection method proposed in this paper is used to screen the training data. And in order to facilitate the selection of high-quality training data,
a quantitative index describing the overall quality of data is needed.

According to the recognition matrix $C$ and its horizontal/vertical projections $Q_h/Q_v$, introduced in Section 2.2.2, the comprehensive quality index for a dataset can be calculated as follows:

\[
Q_t = 1 - \frac{\sum_{i=1}^{L} \sum_{j=1}^{L} C(i,j)}{L^2}
\]

\[
Q_h = 1 - \frac{\sum_{i=1}^{L} Q_h(i)}{L} = 1 - \frac{\sum_{j=1}^{L} Q_v(j)}{L}
\]

where, the value of $Q_h$ is between 0 and 1. The smaller the value of $Q_h$, the worse the quality of training data.

Conversely, the larger the value, the better the quality of the training data.

3.3. Two-blinks detection module

In order to realize the asynchronous control of BCI system, we need to provide a "switch" for the system, so as to facilitate the subjects to switch NCI (no control intention) state and CI (control intention) state (i.e., motor imagination period) autonomously. Considering that the amplitude of blinking signal waveform changes obviously and is easy to detect, the system will use the subject’s autonomous two consecutive blinks as this "switch". And we adopt the blink detection method proposed in section 2.3 to realize two-blinks detection. A sliding time window (4 s) is also needed in the blink detection. If it is in NCI state (i.e., non-motor imagery period), the sliding time window will receive the EOG signal sent by the acquisition device in real time and conduct blink detection on the signal in the window at the same time. When the number of blinks in the sliding time window is greater than or equal to two, the system will think that the subject is about to enter CI state (i.e., motor imagination period) and will not perform blink detection. At this time, the sliding time window will no longer receive new data, and all the original data in the window will be cleared. During the 6 second motor imagery period, subjects can independently determine the type of motor imagery (left, right, foot) according to the GUI interface task.

3.4. ICA spatial filter design module

BCI system based on motor imagery EEG is susceptible to the interference of nonobjection noise. It is necessary to extract the correct MRICs, which represent the motor imagery. In order to obtain effective MRICs, a new automatic selection method of MRICs detection filter is proposed in our previous work (Hu et al., 2017) and its main idea is assume that the MRICs have the maximum projection on the electrodes that are closest to the related motor cortex (i.e., C3, C4 corresponding right left hand).

As we know, the calculation of ICA spatial filters is independent of MI labels. Therefore, given the configuration of EEG channels, any data segments in the collected EEG dataset can be used to calculate the ICA spatial filters. Besides, recent studies concerning MI-BCI have shown that ICA model has better transferability across subjects (Zhou et al., 2016; Yijun Wang and Tzyyping, 2012). It is worth noting that although ICA can effectively isolate some physiological artifacts, but it is very sensitive to some types of non-physiological artifacts, such as the burst electromagnetic interferences and the electrode connection faults, etc. This characteristic make ICA have some unique capabilities in artifact detection.

3.5. Classification module

Researches show that when people are actually moving or imagining, the energy of mu and beta rhythm of the cerebral cortex will rise or falls, which we called event-related synchronization/desynchronization (ERD/ERS). If the subject performs left and right motor imagery, the mu and beta rhythms of the contralateral motor cortex is suppressed. Based on the ERD/ERS phenomenon, a simple classification criterion based on the comparison of variance called zero training classifier (proposed in our previous work (Hu et al., 2017) is used instead of the commonly used machine learning classifier, such as linear discriminant analysis and SVM. Experiments show the recognition rate gap between the simple classifier and the learning classifier is not obvious, but the computational complexity of the latter is obviously increased.

3.6. GUI Control module

After 6 s of motor imagery, features are extracted using ICA spatial filter, combined with zero training classifier to get the type of motor imagery, and the control instruction corresponding to the classification result will be sent to connected client. In this paper, Unity3D tool is used to develop a simulation control System (SCS) which can generate corresponding movement according to the received instructions. The basic flow of SCS operation is shown in Fig. 8. After establishing a TCP connection with the MI-BCI system, SCS will continue to listen to the TCP connection. When receiving the instruction, SCS immediately parses the instruction and controls the virtual green person to move around according to the instruction. Such as, if the received instruction is "right", the virtual green person moves to the right. In the process of
moving, the system continuously detects the collision between the virtual person and the gold coin (i.e., destination). Until the virtual person collides with the gold coin, the task is completed and the system ends.

4. experimental results

4.1. Offline experiment result

4.1.1. Public datasets

The experimental dataset used in this paper is BCI Competition IV Data Set 2b (also known as BCI2008IIb). The dataset includes the left and right hand MI-EEG signal of nine subjects, and each subject provides five datasets: B0#01T, B0#02T, B0#03T, B0#04E, B0#05E (# = 1, 2,...,9, and # denotes the number of nine subjects), of which the first three are training sets and the last two are test sets. The number of single trials contained in each dataset is shown in Table 1. The duration of a single trial is about 8 s, in which 3–7.5 s is the MI period, and there are three channels (C3, Cz, and C4) of EEG signals in each trial (Leeb et al., 2008).

4.1.2. Artifact detection in the single trial

In order to illustrate the effect of STCs on artifact detection, two datasets (B0501T, B0605E) from BCI2008–2b are employed in this section (see Section 4.1.1 for details of involved datasets).

Fig. 9 shows the test results for the dataset B0501T consisting of 120 single trials (60 trials for each of two classes, see Table 1). Therefore, 120 STCs are obtained for the calculation of recognition matrix C and its horizontal and vertical projection Qh and Qv. The Fig. 9(b) shows the accuracy Ac(j) of STCs calculated using Eq. (5). It can be seen that in horizontal projection, only Qh(31) = 0.475 is close to the threshold value (0.5), and the corresponding minimum accuracy Ac(31) is 52.5% (marked by the red circle). Fig. 9(c) shows the EEG signal waveform of the 31st trial of the dataset B0501T, which is used to design the STC(31) yielding the highest accuracy (85.8%, marked by the black circle). It can be observed that the waveform of the 31st trial is almost artifact-free. We checked the remaining trials in dataset B0501T and found that all of them are not severely contaminated by artifacts.

4.1.3. The mislabeled trial detection

As mentioned in Section 1, the mislabeled trials mainly attribute to subject’s distraction, fatigue or lack of experience in performing MI tasks. According to the investigation in this study, the mislabeled trials can be divided into two categories: the first type of mislabeled trial is that amplitude modulation of mu-rhythm is very weak or does not appear in EEG data. The second one is that the trial contains the significant motor related mu rhythm modulation, but the identified MI type is not consistent with the label of the trial. For instance, in Fig. 9(a), there are eight Qh values greater than 95%, and even the Qh values corresponding to 53rd and 99th trials reach 100%, which indicates that all STCs made a wrong classification on these two trials. Fig. 11 depicts their instantaneous energies of the mu rhythm during the MI period (3.5–6 s). According to the ERS/ERD effect related to motor imagery, these two trials should belong to the left-hand MI (class 1), but they are both labeled as the right hand MI (class 2).

Due to a number of inevitable reasons, the mislabeled trials often exist in MI-EEG datasets. Commonly, all mislabeled trials should be eliminated from the training sets, since they provide the wrong information for MI-BCI design. However, for the second type of mislabeled trial, the reuse strategy can be considered instead of simply rejecting, because it often contain useful information related to MI. As the number of MI-BCI training trials is usually limited, the reuse strategy of low-quality training trials deserves special attention.

4.1.4. Comprehensive evaluation of MI-EEG dataset quality

Table 2 shows the quality indexes of the forty-five datasets of nine subjects in BCI2008 IIa calculated using Eq. (9). It can be observed that not only the datasets of different subjects have obviously different qualities; even the qualities of the datasets collected on the same subject also have a big difference. For example, for the five datasets of the 8th and 9th subjects shown in Table 2, the qualities of the first two datasets are significantly lower than the last three datasets, while the quality of the first dataset of 1st subject is significantly higher than the qualities of the last four datasets. Obviously, we should avoid using the low-quality training data in MI-BCI system implementation. So, it is not difficult to imagine that the quality indexes facilitate the selection of appropriate training data, which is crucial to achieve a high-performance MI-BCI system.

4.2. System online experiment result

The experiments are conducted on 12 healthy volunteers (5 males and 7 females) with ages ranging from 22 to 29 years, mean = 24.5. All

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### Table 1

The number of trials of each dataset in BCI2008IIb.

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<th>Subject</th>
<th>B01</th>
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<th>B03</th>
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<th>B07</th>
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</table>
Subjects are graduate students in our laboratory, with normal hearing and normal or corrected-to-normal vision. Subjects sign an informed consent form before the start of the online experiment. The current study receives approval from the Institutional Review Board at Anhui University. Each subject went through five online experiments (three of which had low-quality training data detection module and two without the module), and the intervals between two experiments varied from several days to several months.

Tables 3 and 4 show the time consumed and the number of trials by the twelve subjects in each experiment with and without low-quality training data detection module, respectively. It can be seen from the table that compared with other subjects, the time taken and the number of trials required for subject S1 to successfully reach the end point are the least (It is worth mentioning that the number of trials required for the optimal path to complete the task in BCI system is 9). This is because subject S1 has 7 years of experience in MI-EEG data acquisition, and the EEG data quality of this subject is high, and the recognition rate of offline experiment data can reach 100%. All offline MI-EEG datasets collected by our laboratory are publicly available and can be downloaded from our lab website (Wu and Lv, 2022). In table 4, the average number of trials of subject S7 is the largest (24.7), which is due to the poor recognition effect of the subject’s motion imagery, resulting in the issuance of wrong instructions to make the virtual person deviate from the gold coin. At this time, the subject needs to correct the moving direction in time through multiple motion imagery, so the number of trials increases. Comparing other subjects, when the number of trials required to successfully reach the end point is similar, subject S4 had the highest average time per trial (28.1). We watched the video recorded during the experiment and found that this condition is caused by subject S4 taking too long to rest during the relaxation period under the NCI state of the BCI system. Combining Tables 3 and 4, when the BCI system adopts the low-quality training data detection module, the number of trials required to complete the task is reduced for 12 subjects, among which the effect of subject S2 is the most obvious.

5. Discussion and conclusion

Table 2 shows the offline experimental results of the proposed low-quality training data detection method on the BCI2008 IIa. For the five datasets of the 8th and 9th subjects shown in Table 2, the qualities of the first two datasets are significantly lower than the last three datasets, while the quality of the first dataset of 1st subject is significantly higher than the qualities of the last four datasets. Offline experiments on the public dataset BCI2008IIa demonstrate that our proposed method is feasible and can realize the selection of high-quality training data in the design of MI-BCI system. Table 3 and Table 4 show the online
Fig. 10. The STC experimental results of B0605E dataset. (a) the recognition matrix $C$ and its horizontal and vertical projections; (b) the recognition accuracy $A_c$; (c) and (d) time domain waveforms of the 7th and 66th single trials.

Fig. 11. Mu rhythm energy comparisons of motion-related channels in 53rd and 99th single-trials.
experimental results of 12 trials with and without low-quality training data detection module. And the online result show that all of the subjects are able to successfully use the designed BCI system with real-time responses. In the online analysis, we used a novel low-quality data detection method to classify low-quality training data, and apply this method to the design of asynchronous BCI systems. There are many factors affecting the quality of trial, among which the mislabeled trials are very common. In future work, we will explore whether the mislabeled trials can be reused in online MI-BCI systems through relabeling.

Conflict of Interest

The authors declare that they have no conflicts of interest.

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