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Original Research

Evaluation of an online SSVEP-BCI with fast system setup

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A B S T R A C T

The brain−computer interface (BCI) plays an important role in neural restoration. Current BCI systems generally require complex experimental preparation to perform well, but this time-consuming process may hinder their use in clinical applications. To explore the feasibility of simplifying the BCI system setup, a wearable BCI system based on the steady-state visual evoked potential (SSVEP) was developed and evaluated. Fifteen healthy participants were recruited to test the fast-setup system using dry and wet electrodes in a real-life scenario. In this study, the average system setup time for the dry electrode was 38.40 seconds and that for the wet electrode was 103.40 seconds, which are times appreciably shorter than those in previous BCI experiments, enabling a rapid setup of the BCI system. Although the electroencephalogram (EEG) signal quality was low in this fast-setup BCI experiment, the BCI system achieved an information transfer rate of 138.89 bits/min with an eight-channel wet electrode and an information transfer rate of 70.59 bits/min with an eight-channel dry electrode, showing that the overall performance was close to that in traditional experiments. In addition, the results suggest that the solutions of a multi-channel dry electrode or few-channel wet electrode may be suitable for the fast-setup SSEVP-BCI. This fast-setup SSVEP-BCI has the advantages of simple preparation and stable performance and is thus conducive to promoting the use of the BCI in clinical practice.

1. Introduction

A brain−computer interface (BCI) is designed to establish communication between the brain and external environment without relying on peripheral nerves and muscles.[1,2] The BCI has great application potential in various fields, especially in the healthcare and the medical fields. For example, the BCI has become an established means of reestablishing communication in severely paralyzed patients.[3,4] It is clear that for these patients, the use of a BCI is a process of learning a new task and is therefore related to the plasticity of the central nervous system.[5] In addition, neural rehabilitation or neurorehabilitation is an important aspect of BCI application that aims to promote recovery and functional enhancement in patients with neurological diseases.[6] So far, various BCI-based approaches and treatments have been proposed as neuromodulation interventions to improve the restoration of motor or cognitive functions after neurological injury.[7,8] Furthermore, it has been found that even the short-time use of BCI induces modulations in the structural and functional magnetic resonance imaging of the brain,[9] indicating that the BCI has rapid effects on the brain structure and function through neurofeedback. Overall, the BCI has a positive effect on neural restoration and is a useful tool for neurorestoratology. Among various BCI paradigms, the use of the steady-state visual evoked potential (SSVEP) has advantages in terms of the information transfer rate (ITR) and the amount of training required before use,[10,11] making it user friendly and readily accepted in practical use. The SSVEP-BCI has been found to be available to patients with neurological disorders, such as stroke,[12] amyotrophic lateral sclerosis[13] and Duchenne muscular dystrophy.[14] Moreover, compared with conventional treatment, the use of the SSVEP-BCI can more effectively improve the impaired motor function of stroke patients.[15] The visual stimulation of the SSVEP-

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BCI has been found to change the distribution of cortico-muscular coherence in the primary motor somatosensory cortex and contralateral motor cortex, promoting neuroplasticity after stroke.[16] This indicates that the SSVEP-BCI is useful for neural restoration.

Although the BCI has been widely used in clinical applications, it has shortcomings, especially in terms of user experience. A limitation of the BCI is the system setup as it is a key factor affecting practicality. In most BCI experiments or applications, regardless of the paradigm adopted, the system setup is a necessary but laborious task. The setup generally includes skin preparation, electrode placement, and ensuring that the signal quality is acceptable.[17] Huggins et al found that although patients with neurological injuries have a strong interest in using a BCI, they consider the setup time an important factor when considering using a BCI and find a preparation time of less than 10 minutes to be acceptable.[18,19] Several studies in which the system setup time or electrode preparation time was measured in BCI experiments are listed in Table 1.[20–26] Obviously, the use of a dry electrode contributes to the rapid setup of the BCI system, as it reduces the preparation time and need for cleaning. However, the use of a dry electrode generally results in poor signal quality. In the current clinical application of a BCI, a wet electrode, especially a gel-based electrode, is the first choice because of its low impedance and high signal quality.[27] In fact, in most BCI experiments, whether using a dry or wet electrode, the electrode impedance needs to be adjusted to a certain range before the experiment to ensure signal quality. However, reducing the electrode impedance to an acceptable value is a time-consuming task, often accounting for a large part of the setup time.[26,28] Therefore, if the efficiency of the BCI setup can be raised by simplifying the monitoring of the electrode impedance, the patients' acceptance of a BCI will undoubtedly be improved.

The BCI performance is another factor important to patients considering using a BCI. Simplifying the processing of the electrode impedance during the system setup may degrade the signal quality and therefore the BCI performance. As the decoding algorithm directly dictates the BCI performance, it is crucial to determine a suitable algorithm while simplifying the BCI setup. Benefiting from the characteristics of the SSVEP and the development of decoding algorithms, the SSVEP-BCI has natural advantages in accuracy. Numerous decoding algorithms, including canonical correlation analysis (CCA) and its various optimizations[29] and task-related component analysis and its variants,[30] have been developed. With the development of artificial intelligence, many deep learning models, such as the convolutional neural network (CNN)[31] and EEGNet,[32] have recently been used in electroencephalogram (EEG) analysis. Compared with traditional methods, these methods achieve higher accuracy but have a longer analysis time and require training data. Owing to the difficulty in collecting a large volume of EEG data in practical applications, complex algorithms may encounter obstacles. Conversely, training-free or calibration-free algorithms that do not require calibration data from participants are more acceptable in clinical applications. Moreover, compared with healthy people, patients have higher requirements for the usability and practicability of a BCI. Undoubtedly, if a training-free algorithm can achieve good performance even with low-quality signals, the appeal of an BCI to novices, especially patients with neurological impairments, will be greatly enhanced. To make the SSVEP-BCI more applicable in daily use and clinical practice, the BCI system needs to perform reliably and stably while having improved efficiency in system preparation.

It is clear that the BCI has great potential in neurorestoratology, but many issues need to be solved to bring the BCI out of the laboratory and into clinical practice. Among them, enhancing the practicality and performance of the BCI is a priority. This study examines the effect of a rapid system setup strategy for the SSVEP-BCI. To this end, a wearable SSVEP-BCI system, which comprises wireless EEG collection, multi-target stimulation, and online signal analysis, was developed. Participants who had never used a BCI were recruited to evaluate the BCI performance in a real-life scenario and thus the usefulness of the system.

2. Design of the online SSVEP-BCI system

2.1. Data acquisition

An ESPW308 eight-channel wireless EEG acquisition system (BlueBCI Ltd. Beijing, China) was used to collect the EEG signal in this study. The system is mainly used for scientific activities and is equipped with a small amplifier and a wet-electrode cap. The sampling rate of the amplifier was 1000 Hz. With the wet electrode cap, eight-channel EEG signals (POz, PO3, PO4, PO5, PO6, Oz, O1, and O2) were recorded while the reference and ground electrodes were placed on the forehead. In addition, an elastic eight-channel EEG headband was made using commercial dry electrodes (OpenBCI Inc. NY, USA). When using the dry electrodes, the reference and ground electrodes were placed on the left and right ear lobes, respectively. The headset (including an amplifier, electrode cap or band, and battery) was lightweight and did not apply a large load to the user, as shown in Fig. 1. Specifically, the total weight of the headset was 121 g when using wet electrodes and 98 g when using dry electrodes.

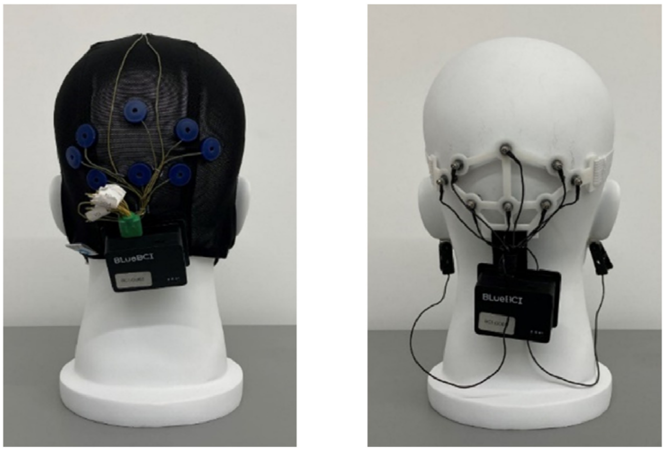
2.2. Stimulus presentation

To achieve multi-target stimulation, the SSVEP-BCI system was designed for a spelling task. The visual stimulation interface was a 4×10 matrix, as shown in Fig. 2. The interface was presented on a 24.5-inch liquid crystal display monitor with a refresh rate of 280 Hz and a resolution of 1920×1080 pixels. Each stimulus was a 165×165-pixel square marked with a character, flickering between white and black. The flickers were coded using a joint frequency and phase modulation method.[33] The frequency and phase are calculated for each stimulus as

Table 1
Comparison of system setup times in different BCI experiments.

BCI experiment	Participant	System setup time	
		Wet electrode	Dry electrode
Gargiulo et al.[20]	healthy	2–3 min per electrode	10 s per electrode
Zander et al.[21]	healthy	–	5 min (3 electrodes)
Grant et al.[22]	patients with altered mental status	12 ± 2 * min (21 electrodes)	–
Chen et al.[23]	healthy	34 min (31 electrodes)	2 min (16 electrodes)
di Fronso et al.[24]	healthy	39 ± 18 * min (64 electrodes)	13 ± 3 * min (64 electrodes)
Hinrichs et al.[25]	healthy	6.36 ± 1.18 * min (19 electrodes)	4.02 ± 0.70 * min (19 electrodes)
Zhao et al.[26]	healthy	–	5.66 min (8 semi-dry electrodes)

*: mean ± SD (standard deviation).



A B

Fig. 1. EEG headset, including an eight-channel wireless amplifier with a (A) wet electrode cap and (B) dry electrode headband.

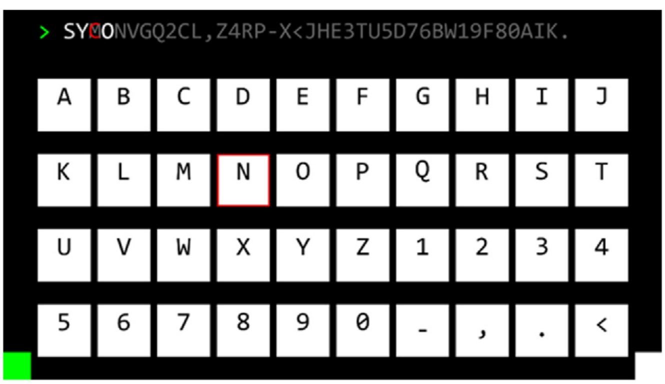


Fig. 2. Visual stimulation interface of 4 × 10 flickers. The gray characters at the top of the interface are targets, the white characters are the correct output, and the red characters are the spelling errors.

$$\begin{cases} f(i,j) = f_0 + \Delta f \times [(i-1) \times 10 + (j-1)] \\ \varphi(i,j) = \Delta\varphi \times [(i-1) \times 10 + (j-1)] \end{cases} \tag{1}$$

where (i,j) represents the flicker located in the i-th row and j-th column ($i = 1,2,3,4$ and $j = 1,2,\cdots,10$), f_0 is 8 Hz, Δf is 0.2 Hz, and $\Delta\varphi$ is 0.5π. The space above the matrix was used to display the spelling results for online feedback. The stimulation was presented using Psychtoolbox (PTB) in MATLAB.

2.3. Data processing

The EEG signal was collected and amplified through the amplifier and then transmitted to a computer through Wi-Fi. To improve the analysis efficiency of the online system, the data segment received by the computer was downsampled to 250 Hz. The signal was then preprocessed to reduce noise. Specifically, a 50-Hz notch filter was used to eliminate power noise, and a bandpass filter was used to extract the effective EEG signal. The upper and lower cutoff frequencies of the bandpass filter were 90 and 5 Hz respectively.

In this SSVEP-BCI system, an online adaptive canonical correlation analysis (OACCA) algorithm, which is a recent and state-of-the-art training-free algorithm proposed by Wong et al.,[34] was adopted. OACCA achieved excellent performance at the World Robot Contest 2022.[35] In fact, OACCA is an integrated algorithm that combines the filter bank CCA (FBCCA) proposed by Chen et al.,[36] prototype spatial filter (PSF) proposed by Lao et al.,[37] and online multi-stimulus CCA (OMSCCA) proposed by Wong et al..[38]

The multi-channel EEG signal in the n-th trial $\mathbf{X}^n$ is first decomposed into N_{band} sub-band signals adopting the filter bank technique. For the j-th sub-band EEG signal in the n-th trial $\mathbf{X}^{\text{subj},n}$, the coefficient of correlation between $\mathbf{X}^{\text{subj},n}$ and reference signal $\mathbf{Y}_k$ is calculated through CCA as

$$\begin{aligned} \left\{ r_k^{\text{subj},n}, \mathbf{u}_k^{\text{subj},n}, \mathbf{v}_k^{\text{subj},n} \right\} &= \underset{\mathbf{u},\mathbf{v}}{\operatorname{argmax}} \frac{\mathbf{u}^T \left(\mathbf{X}^{\text{subj},n}\right)^T \mathbf{Y}_k \mathbf{v}}{\sqrt{\mathbf{u}^T \left(\mathbf{X}^{\text{subj},n}\right)^T \mathbf{X}^{\text{subj},n} \mathbf{u} \cdot \mathbf{v}^T \mathbf{Y}_k^T \mathbf{Y}_k \mathbf{v}}} \\ &= \text{CCA}\left(\mathbf{X}^{\text{subj},n}, \mathbf{Y}_k\right) \end{aligned} \tag{2}$$

where $\mathbf{u}_k^{\text{subj},n}$ and $\mathbf{v}_k^{\text{subj},n}$ are the spatial filters for $\mathbf{X}^{\text{subj},n}$ and $\mathbf{Y}_k$, respectively, and $r_k^{\text{subj},n}$ is the coefficient of correlation between $\mathbf{X}^{\text{subj},n}\mathbf{u}_k^{\text{subj},n}$ and $\mathbf{Y}_k\mathbf{v}_k^{\text{subj},n}$.

In FBCCA, $(n-1) \cdot N_{\text{band}}$ spatial filters ($\tilde{\mathbf{u}}^{\text{sub}1,1}$, $\tilde{\mathbf{u}}^{\text{sub}1,2}$, $\cdots$, $\tilde{\mathbf{u}}^{\text{sub}N_{\text{band}},n-1}$) are obtained after the determination of $n-1$ trials. As PSF is defined as the spatial filter with the greatest similarity to all filters from previous trials, the PSF of the j-th sub band in the n-th trial is calculated as

$$\mathbf{u}_0^{\text{subj},n} = \underset{\mathbf{u}}{\operatorname{argmax}} \frac{\mathbf{u}^T \sum_{m=1}^{n-1} \tilde{\mathbf{u}}^{\text{subj},m} \left(\tilde{\mathbf{u}}^{\text{subj},m}\right)^T \mathbf{u}}{\mathbf{u}^T \mathbf{u}} = \underset{\mathbf{u}}{\operatorname{argmax}} \frac{\mathbf{u}^T \mathbf{S}^{\text{subj},n-1} \mathbf{u}}{\mathbf{u}^T \mathbf{u}} \tag{3}$$

where $\mathbf{S}^{\text{subj},n-1}$ is obtained through continuous iteration as

$$\mathbf{S}^{\text{subj},n-1} = \mathbf{S}^{\text{subj},n-2} + \tilde{\mathbf{u}}^{\text{subj},t-1} \left(\tilde{\mathbf{u}}^{\text{subj},t-1}\right)^T \tag{4}$$

OMSCCA aims to learn a common spatial filter from the user's multi-stimulus SSVEP templates. Similar to Equation (2), OMSCCA corresponding to the j-th sub-band EEG signal in the n-th trial is described by

$$\begin{aligned} \left\{ \mathbf{w}_x^{\text{subj},n}, \mathbf{w}_y^{\text{subj},n} \right\} &= \underset{\mathbf{u},\mathbf{v}}{\operatorname{argmax}} \frac{\mathbf{u}^T \sum_{m=1}^{n-1} \left(\mathbf{X}^{\text{subj},m}\right)^T \mathbf{Y}_{\hat{k}^m} \mathbf{v}}{\sqrt{\mathbf{u}^T \sum_{m=1}^{n-1} \left(\mathbf{X}^{\text{subj},m}\right)^T \mathbf{X}^{\text{subj},m} \mathbf{u} \cdot \mathbf{v}^T \mathbf{v}}} \\ &= \underset{\mathbf{u},\mathbf{v}}{\operatorname{argmax}} \frac{\mathbf{u}^T \mathbf{C}_{XY}^{\text{subj},n-1} \mathbf{v}}{\sqrt{\mathbf{u}^T \mathbf{C}_{XX}^{\text{subj},n-1} \mathbf{u} \cdot \mathbf{v}^T \mathbf{v}}} \end{aligned} \tag{5}$$

where $\mathbf{w}_x^{\text{subj},n}$ and $\mathbf{w}_y^{\text{subj},n}$ are the OMSCCA spatial filters (OMSCCA-SFs) of the j-th sub-band signal, and $\mathbf{C}_{XX}^{\text{subj},n-1}$ and $\mathbf{C}_{XY}^{\text{subj},n-1}$ are the sum of covariance matrices from existing trials obtained as

$$\begin{cases} \mathbf{C}_{XX}^{\text{subj},n-1} = \mathbf{C}_{XX}^{\text{subj},n-2} + \left(\mathbf{X}^{\text{subj},n-1}\right)^T \mathbf{X}^{\text{subj},n-1} \\ \mathbf{C}_{XY}^{\text{subj},n-1} = \mathbf{C}_{XY}^{\text{subj},n-2} + \left(\mathbf{X}^{\text{subj},n-1}\right)^T \mathbf{Y}_{\hat{k}^{n-1}} \end{cases} \tag{6}$$

The correlation coefficients of the FBCCA, PSF, and OMSCCA for the sub-band signals are then calculated as

$$\begin{cases} r_k^{\mathrm{subj},n} = \mathrm{CCA}\left(\mathbf{X}^{\mathrm{subj},n}, \mathbf{Y}_k\right) \\ \dot{r}_k^{\mathrm{subj},n} = \mathrm{CCA}\left(\mathbf{X}^{\mathrm{subj},n}\mathbf{u}_0^{\mathrm{subj},n}, \mathbf{Y}_k\right) \\ \ddot{r}_k^{\mathrm{subj},n} = corr\left(\mathbf{X}^{\mathrm{subj},n}\mathbf{w}_x^{\mathrm{subj},n}, \mathbf{Y}_k\mathbf{w}_y^{\mathrm{subj},n}\right) \end{cases} \tag{7}$$

where CCA() is the calculation of the similarity of two matrices and $corr()$ is the calculation of the correlation between two vectors. The results of all sub-band signals in the n-th trial are combined according to

$$\tilde{r}_k^n = \sum_{j=1}^{N_{band}} \left(j^{-a} + b\right) \cdot \left(r_k^{\mathrm{subj},n} + \dot{r}_k^{\mathrm{subj},n} + \ddot{r}_k^{\mathrm{subj},n}\right) \tag{8}$$

where a is 1.25 and b is 0.25 according to Chen et al.'s study.[36] The label corresponding to the maximum $\tilde{r}_k^n$ is thus the result of the n-th trial in OACCA. In this study, N_{band} for online SSVEP identification is set at 5 to achieve better classification, whereas other parameters are consistent with those of the original OACCA.

3. Experimental design

3.1. Participants

Fifteen healthy participants (seven men and eight women with an average age ± standard deviation (SD) of 27.07 ± 5.82 years) who had normal (or corrected-to-normal) vision were recruited in this study. None of the participants had used an SSVEP-BCI before. Before the experiment, all participants understood the experimental content and procedure and provided written informed consent. The study was approved by the Institutional Review Board of the University of Hong Kong/Hospital Authority Hong Kong West Cluster.

3.2. System setup

The SSVEP-BCI system was tested in a quiet, naturally lit room to simulate a usage scenario in real life. The participants did not perform any skin preparation or hair cleaning before the experiment. To ensure a rapid system setup, the preparation time (from putting on the EEG acquisition device to starting the experiment) was specified. In the experiment using wet electrodes, the preparation time was required to be no more than 3 minutes. The researchers injected a small amount of conductive gel into the gap between the scalp and electrodes and stirred the hair until the participant felt the gel on the scalp, and they then asked the participant to blink and clench their teeth. In the experiment using dry electrodes, the preparation time was required to be no more than 2 minutes. The researchers moved the participant's hair to allow the dry electrodes to make contact with the scalp and then asked the participant to clench their teeth. In this study, we did not monitor the electrode impedance whether using wet or dry electrodes. The EEG acquisition system was deemed to be working properly when obvious artifacts caused by blinking or teeth clenching were observed in the real-time signal, and the experiment then began. The overall setup time from the electrode placement until the beginning of experiment was recorded.

3.3. Protocol

Each participant completed 10 blocks of the online SSVEP-BCI experiment with a cue-guided spelling task, where dry electrodes were used in the first five blocks and wet electrodes were used in the second five blocks. Each block comprised 40 trials corresponding to 40 stimulus targets. The trial began with a 1-second cue. During this period, the BCI system randomly selected a target, and the character corresponding to the target appeared in a red box. The participant moved the sight to the target character as quickly as possible. All characters then flickered for 3 seconds, and the target character remained cued by the red box. The trial ended with a 1-second rest, during which the target character was identified by the online algorithm and displayed on the interface for visual feedback. During the flickering process, the participant was asked to avoid making head movements and blinking. The duration of each block was approximately 4 minutes, with a 3-minute interval to allow the participant to rest. After completing the five dry-electrode blocks, the participant rested for 30 minutes before starting the wet-electrode blocks. After completing all the blocks, the participant was required to answer a question on wearing comfort (Question: Which electrode do you think is more comfortable? A. The wet electrode, B. The dry electrode, C. The two electrodes are similar in comfort).

3.4. Metrics

As the experiment was conducted with a fast BCI system setup, the signal quality may differ from that in other studies. In the present study, a wide-band signal-to-noise ratio (SNR) was adopted to evaluate the quality of the SSVEP data. Compared with the conventional narrow-band SNR, the wide-band SNR is considered to characterize better both the wide-band noise and the contribution of harmonics to the signal.[39] The wide-band SNR is calculated as

$$\mathrm{SNR} = 10\log_{10}\frac{\sum_{k=1}^{N_h} P(k\cdot f)}{\sum_{f=0}^{f_s/2} P(f) - \sum_{k=1}^{N_h} P(k\cdot f)} \tag{9}$$

where N_h is the number of harmonics, f_s is the sampling frequency, and $P(f)$ is the power spectrum at frequency f. In the adoption of the wide-band SNR, the sum of the power spectrum of multiple harmonics is considered as the desired signal. N_h was set at 5 in this study.

The classification accuracy and ITR were used to evaluate the performance of the SSVEP-BCI system. Accuracy is expressed as the ratio of the number of trials in which the BCI system output a correct target to the total number of trials. ITR is a metric commonly used to evaluate the BCI performance and comprehensively considers the accuracy, number of targets, and target selection time. The ITR is calculated as

$$\mathrm{ITR} = \left(\log_2 K + P\log_2 P + (1-P)\log_2\left(\frac{1-P}{K-1}\right)\right)\cdot 60 \Big/ T \tag{10}$$

where K is the number of targets, P is the classification accuracy, and T is the average time required for the BCI system to complete a target selection, including the gaze time (typically the data length of the SSVEP signal) and gaze shift time. In the online experiment, T, including the cue time, gaze time and feedback time, was fixed at 5 seconds. In offline analysis, in addition to the data length of the SSVEP signal, a gaze shift time of 0.55 seconds was included in the calculation of the ITR[36] to simulate actual practice. Moreover, in addition to eight-channel EEG signals, a three-channel signal (Oz, O1, and O2) and a one-channel signal (Oz) were used in offline analysis.

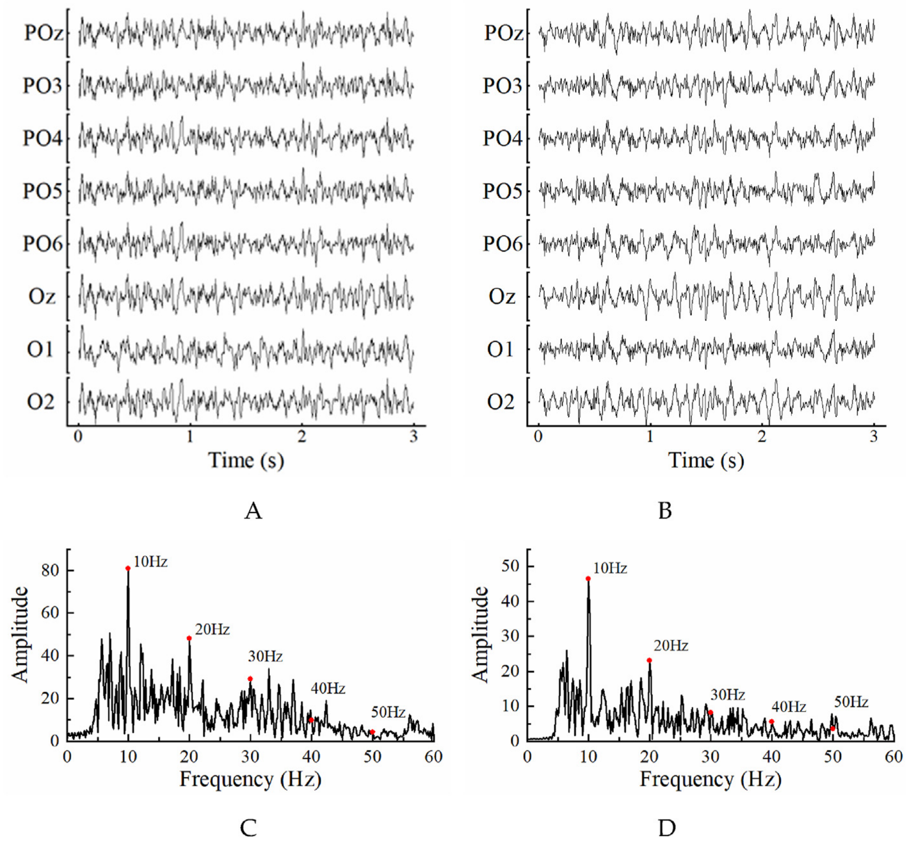


Fig. 3. EEG signal and amplitude spectrum of a participant in a trial with a stimulation frequency of 10 Hz: (A) signal recorded by the wet electrode, (B) signal recorded by the dry electrode, (C) amplitude spectrum of the average signal in (A), and (D) amplitude spectrum of the average signal in (B).

4. Results

4.1. Setup time and signal quality

The average setup time for the 15 participants when using the dry electrode was 38.40 ± 9.85 s whereas the average setup time when using the wet electrode was 103.40 ± 20.57 s. A paired t-test indicated a significant difference in the setup time between the two types of electrode ($p < 0.001$). Regarding the wearing comfort of the electrodes, 10 of the 15 participants thought that the wet electrodes were more comfortable in this study (proportion: 67%), five participants thought that the two electrodes were similar in comfort (proportion: 33%), and none of the participants that the dry electrodes were more comfortable (proportion: 0%).

Fig. 3 presents an example of eight-channel EEG signals of a participant recorded by wet and dry electrodes after band-pass filtering. Clearly, in the fast-setup BCI experiments, the similarity of EEG signals was high across different channels, whether the signals were collected by wet or dry electrodes. In addition, there was appreciable noise in the EEG signals for both types of electrode. The eight-channel signals in each trial were averaged to calculate the frequency spectrum. The results are shown in Fig. 3. In the two trials, the SSVEP responses of the wet electrode signal and dry electrode signal were strong at the fundamental frequency and the second harmonic frequency, but the response at higher harmonics was overwhelmed by noise.

The wide-band SNR in each trial was calculated from the SSVEP spectra and then averaged across all blocks and participants. The average SNRs of the wet electrode signal and dry electrode signal are shown in Fig. 4. The data collected in this study were compared with a benchmark dataset collected by a research-grade EEG system with wet electrodes.[40] The stimulus frequency used in the benchmark dataset is consistent with that used in this study, and the layout of the stimulation interface is similar to that used in this study. In contrast with this study, the benchmark dataset was collected in a dimly lit soundproof room, with the electrode impedances below 10 kΩ. To make a valid comparison, 3-second EEG segments after the onset of stimulation in the benchmark database were selected, and the same eight channels used in the fast-setup system were selected for analysis. As shown in Fig. 4, the wide-band SNRs of the wet electrode signal and dry electrode signal in this study are similar,

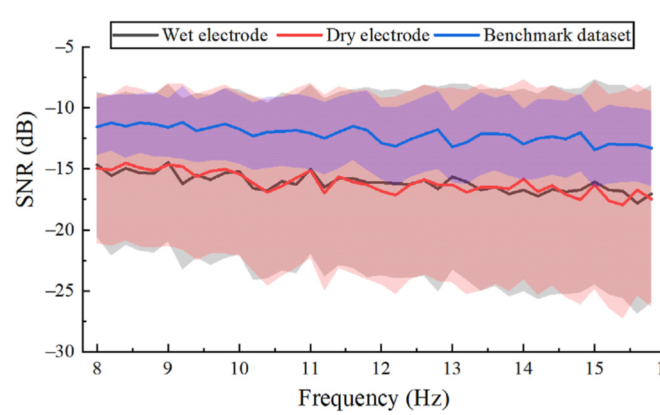


Fig. 4. Wide-band SNR corresponding to 40 stimulus frequencies (from 8 to 15.8 Hz at intervals of 0.2 Hz) for the data of wet and dry electrodes in this study and the benchmark dataset. The shaded areas represent the standard deviation (SD).

both being much lower than the SNR in the benchmark dataset. In addition, the relationship between the SNR and stimulus frequency is illustrated in Fig. 4. Both the two electrode signals in this study and the benchmark dataset showed a general declining tendency of the wide-band SNR with the stimulus frequency, which is consistent with the results of Liu et al..[39] In general, the SNR-based analysis confirms that the wearable EEG acquisition system used in this study effectively captured EEG signals with simplified preparation. However, there is no doubt that the quality of our signals is much worse than that of datasets acquired under laboratory conditions.

4.2. Online experiment

Table 2 presents the classification accuracy and ITR of the 15 participants in the online BCI experiment. Although the SNRs of the wet and dry electrode signals were similar, the BCI performance based on single-trial classification differed greatly between the wet and dry electrodes. The average classification accuracy of the wet electrode exceeded 90% and was 20% higher than that of the dry electrode. The ITR of the wet electrode was 18 bits/min higher than that of the dry electrode. The results of paired t-tests indicate that the differences between wet and dry electrodes in accuracy and ITR were significant (both $p < 0.01$). In addition, there were strong individual differences between the wet and day electrodes. There were eight participants for whom the accuracy difference between wet and dry electrodes was less than 10% (proportion: 53%) whereas there were four participants for whom the accuracy difference was 50% or greater (proportion: 27%).

The relationship between the SNR and classification accuracy for the present fast-setup SSVEP-BCI system is explored using the results presented in Fig. 4 and Table 1. The relationship is shown in Fig. 5, which is a scatter plot of the SNR versus the ITR for the wet and dry electrodes. Although the scatter distribution for the wet electrode is different from that for the dry electrode, their fitted lines indicate that the accuracy of the two electrodes was generally positively correlated with the SNR. For the wet electrode, the Pearson correlation coefficient between the SNR and accuracy is $r = 0.501$ with $p = 0.057$, indicating an insignificant positive correlation between them. However, there is significant positive correlation between the SNR and accuracy for the dry electrode ($r = 0.738$, $p = 0.002$). Furthermore, the relationship between the SNR difference and accuracy difference of the two electrode signals for each participant is shown in Fig. 6. In this fast-setup BCI, the SNR of the dry electrode signal is even better than that of the wet electrode signal for some participants. However, the accuracy of the wet electrode signal exceeds that of the dry electrode signal for almost all participants. The Pearson correlation coefficient between the SNR difference and the accuracy difference is $r = 0.312$ with $p = 0.258$, indicating that the two variables have low correlation without significance.

Table 2
Accuracy and ITR of the 15 participants in the online BCI experiment.

Participant	Wet electrode		Dry electrode	
	Accuracy (%)	ITR (bits/min)	Accuracy (%)	ITR (bits/min)
S1	99.50	63.14	96.50	59.53
S2	91.00	53.11	74.50	38.22
S3	99.50	63.14	23.00	5.86
S4	99.50	63.14	96.00	58.67
S5	100.00	63.86	95.00	57.55
S6	92.00	54.63	36.50	12.47
S7	95.50	57.90	62.50	29.03
S8	97.00	59.78	97.00	60.03
S9	100.00	63.86	96.50	59.43
S10	99.00	62.42	97.00	59.82
S11	86.00	48.18	36.00	12.03
S12	96.00	58.50	87.50	49.67
S13	88.00	49.70	82.00	44.35
S14	81.00	43.66	24.00	6.30
S15	61.00	27.64	30.00	9.02
Mean ± SD	92.33 ± 10.46	55.51 ± 10.02	71.71 ± 29.42	37.46 ± 22.60

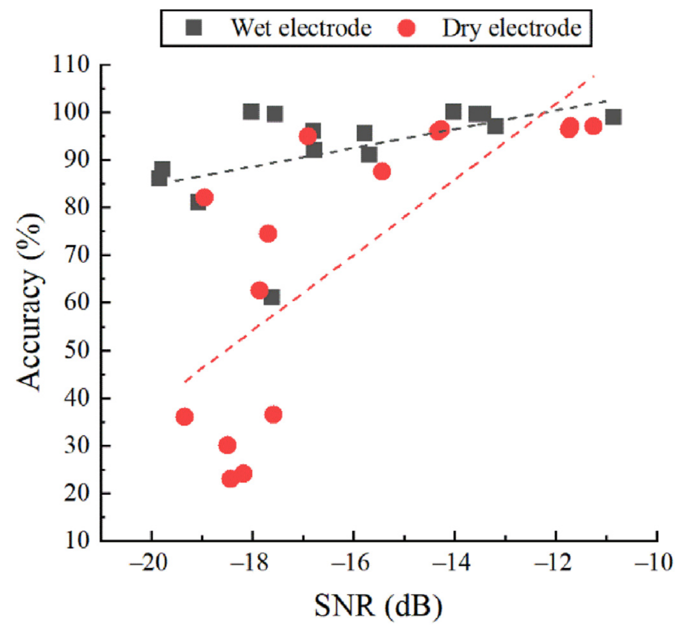


Fig. 5. Relationship between the SNR and classification accuracy. The dashed lines are linearly fitted on the data.

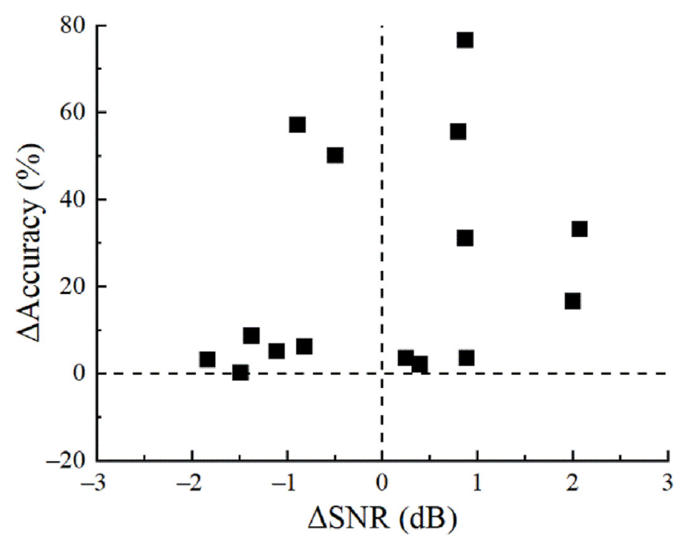
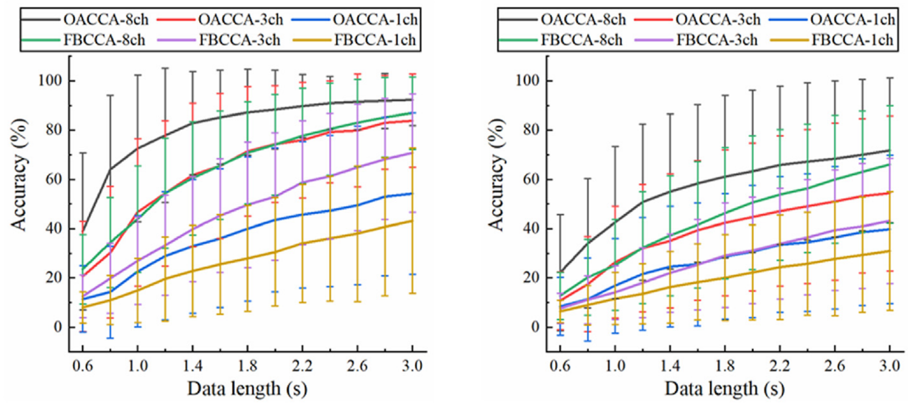


Fig. 6. Relationship between the SNR difference and accuracy difference between wet and dry electrode signals for each participant. The SNR difference is the SNR of the wet electrode signal minus that of the dry electrode signal, and the accuracy difference is the classification accuracy of the wet electrode signal minus that of the dry electrode signal.

4.3. Offline analysis

To further determine the capability of the fast-setup SSVEP-BCI system, the classification performance of OACCA was evaluated in offline analysis. FBCCA, which is a commonly used training-free algorithm for SSVEP identification, was adopted for comparison.



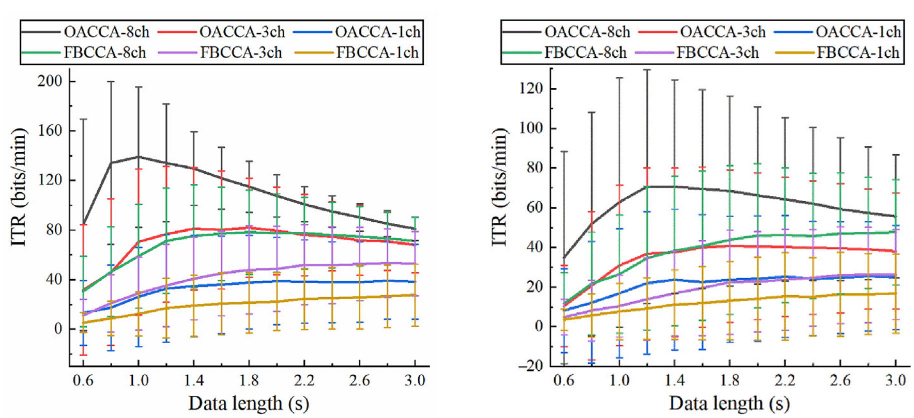
A B

Fig. 7. Classification accuracy of the OACCA and FBCCA across all participants on different channels with different data lengths (from 0.6 to 3 s with intervals of 0.2 s) for (A) wet electrodes and (B) dry electrodes. The error bars denote the SD.

Fig. 7 presents the average accuracy of these two algorithms on the wet and dry electrode data and Fig. 8 presents the ITR. As the data length increases, the algorithm accuracy increases, reaching a maximum value at 3 s (wet: OACCA/eight channels: 92.33%, OACCA/three channels: 83.77%, OACCA/one channel: 54.23%, FBCCA/eight channels: 86.93%, FBCCA/three channels: 70.70%, OACCA/one channel: 43.17%; dry: OACCA/eight channels: 71.71%, OACCA/three channels: 54.30%, OACCA/one channel: 39.73%, FBCCA/eight channels: 65.97%, FBCCA/three channels: 43.07%, OACCA/one channel: 30.87%). The highest ITR in different cases is achieved at different data lengths (wet: OACCA/eight channels: 138.89 bits/min at 1.0 s, OACCA/three channels: 81.78 bits/min at 1.8 s, OACCA/one channel: 39.22 bits/min at 2.8 s, FBCCA/eight channels: 78.25 bits/min at 1.8 s, FBCCA/three channels: 53.21 bits/min at 2.8 s, FBCCA/one channel: 27.53 bits/min at 3.0 s; dry: OACCA/eight channels: 70.59 bits/min at 1.2 s, OACCA/three channels: 40.65 bits/min at 1.8 s, OACCA/one channel: 25.38 bits/min at 2.8 s, FBCCA/eight channels: 47.54 bits/min at 3.0 s, FBCCA/three channels: 26.21 bits/min at 3.0 s, FBCCA/one channel: 16.74 bits/min at 3.0 s). It is impressive that OACCA outperforms FBCCA under all conditions.

Undoubtedly, as the number of channels decreases, the performance of SSVEP decoding algorithms generally becomes worse. An interesting finding from Figs. 7 and 8 is that for the wet electrode, the performance of OACCA on three channels is almost the same as that of FBCCA on eight channels. For dry electrodes, the performances of OACCA on three channels and FBCCA on eight channels are similar, as are OACCA on one channel and FBCCA on three channels. Clearly, compared with the adoption of FBCCA, the adoption of OACCA helps to reduce the number of electrodes used in the BCI system, thereby enhancing system practicability.

Fig. 8 shows that the fast-setup system has a maximum ITR at 1.0 s with the eight-channel wet electrode after averaging across the 15 participants, but this value may not represent the potential optimal performance of the system, as the data length corresponding to the highest ITR is different for each participant. To explore the optimal performance of this BCI system, the highest ITR of each participant was selected by averaging the ITR values by block. The highest ITR was then averaged across all participants. A paired t-test was conducted to evaluate the pairwise difference among different electrode configurations (the type of electrode and the number of channel). The result is shown in Fig. 9. It is clear that the eight-channel wet electrode performs best, far outperforming other solutions. The second-best solution is the three-channel wet electrode. The average best ITR of the three-channel wet electrode seems to be larger than that of the eight-channel dry electrode, but the t-test shows that the difference is not significant. Another comparison without a significant difference is that between the one-channel wet electrode and the three-channel dry electrode.



A B

Fig. 8. ITR of the OACCA and FBCCA across all participants on different channels with different data lengths (from 0.6 to 3 s in intervals of 0.2 s) for (A) wet electrodes and (B) dry electrodes. A gaze shift time of 0.55 s was included in the calculation of ITR. The error bars denote the SD.

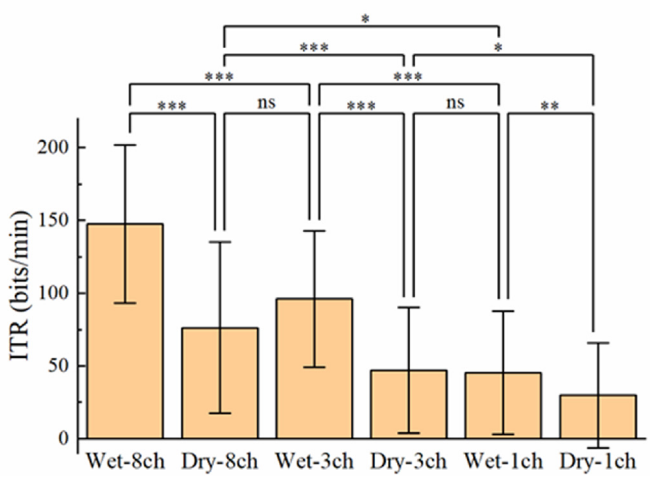


Fig. 9. Average of the highest ITR for 15 participants under different electrode configurations. The significance of the difference between two configurations is marked by ns ($p \geq 0.05$), * ($p < 0.05$), ** ($p < 0.01$), or *** ($p < 0.001$).

Therefore, fewer wet electrodes than dry electrodes are required for the same or similar classification performance of the BCI system.

5. Discussion

This study presented a fast-setup SSVEP-BCI, which was equipped with a miniature, wireless EEG device and an advanced decoding algorithm to achieve multi-target identification. The basis for the rapid BCI setup was a portable EEG device. Consumer-grade EEG collectors have been used to simplify operation and reduce costs in previous studies. Compared with Liu et al.'s study,[41] in which Emotive EPOC was used, and Dilshad et al.'s study,[42] in which an OpenBCI device was used, the present study has an overwhelming advantage in terms of ITR, which may be due to the fact that the signal quality and decoding algorithm in other studies were not as good as those in the present study. When consumer-grade devices are set up normally and work with low electrode impedance, the waveforms they collect can be close to those of research-grade devices.[43,44] However, in terms of system setup, they generally take several minutes or even longer than 10 minutes to set up.[45,46] In addition, these devices are sensitive to environmental interference,[46] making them less suitable for quick setup, as this operation likely leads to unstable connections and thus experimental failure. In this study, such failures did not occur, indicating that all components of the BCI system worked normally during the experiment.

Compared with conventional BCI experiments, the system setup time in this study was substantially reduced. In particular, taking the results of Gargiulo et al.'s study[20] as a reference, the preparation time was shortened, especially when using the wet electrode. According to Huggins et al.'s survey, the ideal setup time for a BCI for clinical use was less than 10 minutes, but when the setup time was greater than 20 minutes, the proportion of respondents willing to use a BCI dropped to 74%.[18] It is clear that simplicity of the system setup is an important factor of user willingness to use a system in clinical BCI applications. There is no doubt that when using the fast-setup BCI, the system setup is no longer a factor affecting the patient willingness to use the BCI.

In this study, the BCI setup was accelerated by eliminating electrode impedance monitoring. Consequently, the signal quality was worse than that obtained under normal experimental procedures. The wide-band SNRs of the wet and dry electrodes were comparable in this study (wet: -16.12 ± 0.74 dB; dry: -16.13 ± 0.90 dB), both being significantly lower than the SNR of the benchmark dataset (-12.19 ± 0.64 dB). It is noted that the SNR of the benchmark database calculated in this study is slightly different from the value given by Liu et al.,[39] owing to the difference in the calculation details in the two studies. In addition, a large standard deviation of the SNR demonstrates an appreciable fluctuation in the signal quality in this study, which may be due to large inter-individual differences caused by unstable and non-robust contact between the electrodes and scalp under fast-setup operation. Nonetheless, with an advanced decoding algorithm, this system still has good BCI performance. The results show that OACCA outperforms the classic FBCCA in this study. In Wong et al.'s study,[34] OACCA outperformed FBCCA on three datasets collected under normal conditions. The present study confirmed that OACCA performs well even for lower signal quality. The performance of the fast-setup BCI system in this study (40 targets, eight channels) is even better than that of FBCCA on the BETA dataset (40 targets, nine channels)[39] and that of FBCCA on a benchmark dataset (40 targets, nine channels),[40] where wet electrodes were used to collect data for each dataset. This confirms that the advantage of the algorithm covers the shortcoming of poor signals to a certain extent and thus enables a quickly setup BCI system to perform similarly to conventionally setup BCI systems, enhancing the usability of the quickly setup BCI system in real-life applications. In surveys conducted for patients with neurological injuries, all patients were satisfied when the BCI achieved an output of 25 letters per minute.[18,19] In the present study, the accuracy of OACCA on the eight-channel wet electrode signal with a length of 1 s was 72.53%. Considering the gaze time of 0.55 s, it is inferred that the spelling system based on the fast-setup BCI correctly outputs 28 characters in 1 minute, which exceeds the expectation of patients. Therefore, this SSVEP-BCI system would be well accepted and have high application potential in clinical practice. A study that only focused on the wearing comfort of EEG electrodes without analyzing signal quality found that there was no significant difference in preparation time between experienced therapists and inexperienced relatives in helping stroke patients put on the electrode headset.[47] The time required for patients to put on the headset in that study was close to the system setup time in this study. We believe that the current BCI system will work well when used at home by patients, as long as there is a relative or caregiver to help with mounting the headset. Overall, the fast-setup SSVEP-BCI meets the needs of patients in terms of both system setup and BCI performance.

Both dry and wet electrodes were evaluated in the rapid setup BCI. A dry electrode has clear advantages in system setup, whereas a wet electrode seems to be more popular in terms of comfort. In this study, although the wide-band SNR of the wet electrode signal was numerically close to that of the dry electrode signal, the accuracy of the wet electrode signal was better than that of the dry electrode signal. A positive correlation is generally observed between the SNR and classification accuracy of an SSVEP-BCI.[48] Similarly, there was a positive correlation between the SNR and accuracy for both the wet and dry electrodes in this study. However, the correlation was not necessarily significant, which is similar to the results of Jiang et al.[49] The significant relationship between the SNR and accuracy may depend on the data collected. The results indicate that, for the same electrode, higher accuracy generally corresponds to a higher SNR. However, for different electrodes, there seems to be no strong correlation between the SNR and accuracy. This may be due to the different characteristics of the signals from different electrodes caused by non-robust contact between the electrodes and scalp under a fast setup. In fact, even though the EEG signals collected by some portable devices are close in shape to those collected by professional devices, the classification results are worse.[43] In the case of the fast-setup BCI, the signals collected by both dry and wet electrodes are mixed with a lot of noise, making their SNR values similar. However, the distribution of noise in signals may differ for different electrodes, leading to differences in classification accuracy. Therefore, the SNR is found not to strongly relate to the accuracy of the fast-setup BCI.

In real-life applications, a reasonable electrode configuration can help improve the practicality of the BCI. In this study, among the six electrode configurations involving the type and number, the eight-channel wet electrode naturally performed best. It is known that the BCI performance of a wet electrode is generally better than that of a dry electrode, and the BCI performance is positively related to the number of channels. It was found in this study that there was no significant difference in the highest ITR between the three-channel wet electrode and the eight-channel dry electrode or between the one-channel wet electrode and the three-channel dry electrode. It seems that, when using dry electrodes for EEG acquisition, the difference in signal quality between dry and wet electrodes is compensated to a certain extent by increasing the number of electrodes. Moreover, for a 40-target BCI, accurate discrimination based on few-channel electrodes (one or three channels) may be hard to achieve, especially when using dry electrodes. However, when using a BCI to control external devices, it is appropriate to use three-channel or single-channel electrodes owing to the relatively small number of commands required for output. The use of fewer electrodes means a shorter system preparation time. Moreover, reducing the number of channels lowers the requirements for amplifier channels and reduces the hardware cost. Taking into account experimental preparation, system performance and user experience, the solutions of few-channel wet electrodes and multi-channel dry electrodes are suitable for an SSVEP-BCI in real application. It is believed that this electrode configuration strategy, combined with simplified system operation, can make the BCI more readily accepted and used by patients.

A number of clinical studies have provided evidence that a BCI helps patients with neural rehabilitation and communication with the outside world. In the SSVEP paradigm, the BCI is frequently developed as a communication tool owing to its high ITR and support for rich command output. The BCI is of great help to patients who cannot communicate normally. A BCI allows them to express their thoughts independently, thereby improving their quality of life. Furthermore, the repeated use of a BCI improves the damaged neurological function to a certain extent.[6] In neural rehabilitation, an SSVEP-BCI enhances the ability of impaired extremities by inducing neural plasticity and repairing the motor nerve pathway.[50] Combined with the use of an SSVEP-BCI, conventional treatments, such as the adoption of rehabilitation robots and functional electrical stimulation, can be developed into a more effective neural rehabilitation for severe neurological injuries. Obviously, if patients use a BCI daily, there will be a positive effect on their recovery of body functions. As the fast-setup BCI in this study helps reduce barriers that currently hinder patients from using a BCI, we believe that it can play a role in facilitating neural restoration in patients.

There are limitations to the present study. Although the quick setup in this study can reduce the preparation time for BCI experiments, hair must be cleaned afterward when a wet electrode is used, which takes some time. Moreover, several participants reported that the comfort of the dry electrodes was not as good as that of the wet electrodes as the dry electrodes used in this study had a hard body with fingers that pushed apart the hair to make contact with the scalp. Complaints about the discomfort of this dry electrode was also made by stroke patients in Jochumsen et al.'s study.[47] With the development of materials and manufacturing technology, various dry electrodes have been developed.[51] Among them, some products, such as a dry electrode fabricated from flexible conductive polymer[52] and a semi-dry electrode comprising an Ag/AgCl base and hydrogel probe,[53] would have advantages in terms of comfort. It is claimed that these electrodes perform well under normal preparation procedures, but their performance under a simplified setup is unclear. Our future work will be to test other dry electrodes in evaluating their suitability for a fast-setup BCI based in terms of BCI performance and wearing comfort.

6. Conclusions

In this study, a wearable SSVEP-BCI system with a lightweight headset and high-performance training-free decoding algorithm was proposed, and the effect of simplifying the system setup on the performance of this wearable SSVEP-BCI was investigated. Compared with preparation times in conventional BCI experiments, the preparation time of the fast-setup BCI was greatly shortened. Although the EEG signal quality declined, the BCI achieved good classification owing to the use of the advanced OACCA algorithm. The fast-setup BCI had a performance similar to that of a BCI in conventional experiments and thus meets the needs of patients. The performances of wet and dry electrodes in the fast-setup BCI were compared in this study. It is believed that the solutions of a multi-channel dry electrode and a few-channel wet electrode are suitable for the fast-setup SSEVP-BCI, in terms of the simplicity of operation and BCI performance. Overall, the fast-setup BCI system has the advantages of strong wearability, simple preparation, and stable performance and is thus conducive to improving the neurological function and quality of life of patients using a BCI in clinical practice and daily life.

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Authors' contributions

Conceptualization, X.L. and J.W.; methodology, X.L. and J.W.; software, F.W.; validation, Y.H. and F.W.; formal analysis, X.C.; investigation, X.L. and X.C.; resources, W.H.; data curation, X.C.; writing—original draft preparation, X.L. and J.W.; writing—review and editing, X.L. and J.W.; visualization, X.C. and Y.H.; supervision, M.T. and S.X.; project administration, X.L. and S.X.; funding acquisition, X.L., W.H., M.T. and S.X. All authors have read and agreed to the published version of the manuscript.

Acknowledgments

None.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability statement

The data presented in this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy.

Ethical approval

This study was approved by the Institutional Review Board of the University of Hong Kong/Hospital Authority Hong Kong West Cluster (UW 20−221).

Informed consent

All participants were informed and signed their written consent for this work.

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