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A Novel Real-Time Multi-Phase BCI Speller Based on Sliding Control Paradigm of SSVEP

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ABSTRACT Speller had been proved that it's a kind of well interactive manners for brain computer interface (BCI) system. In this study, we proposed a novel steady-state visual evoked potential (SSVEP) BCI speller developed for numerical input. Based on a previous off-line method of SSVEP recognition, a sliding control protocol was used for our real-time spelling task. For ten subjects, on-line experiments of 10 consecutive number inputs were conducted for two different control conditions. In contrast to traditional static protocol of multi-phase SSVEP signal extraction, the average information transmission rate (ITR) of sliding control protocol reached 23.45 bits/min, higher than that of traditional static protocol (19.85 bits/min). The results showed the validity and high-efficiency of sliding control paradigm for a real-time multi-phase SSVEP speller.

INDEX TERMS BCI, speller, multi-phase, sliding control paradigm, SSVEP.

I. INTRODUCTION

Over the past few years, BCI technology has got rapid increase attention on the development of relevant studies. EEG-based BCI system builds a novel transmission channel between the human brain and external devices by commands control without body movement [1]–[4]. Among these systems, BCI-speller can be considered as one of the first proposed applications and has opened the door for technology improvement in the field [5]–[7].

Generally, speller systems are based on neurophysiological protocols such as event-related potentials (e.g., P300) [8]–[12], event-related desynchronization/synchronization (ERD/ERS) [13]–[17] and steady-state evoked potentials (SSVEPs) [18]–[22]. Among these patterns, it has been verified that SSVEP has more precise classification accuracy and better performance than those of other patterns of EEG signals [23]–[26]. And SSVEP-based BCI devices are largely investigated for real applications.

For SSVEP speller, visual stimulus is characterised by positive and negative fluctuations to evoke corresponding EEG patterns with a specific stimuli in a graphic user interface (GUI) [27]. The user needs to focus on the target stimuli on behalf of the appropriate character. The advantage of this way is that it does not require training time for model calibration [25]. And the stimulus number is greatly increased for improving the speed of BCI speller [28]. Consequently, the development of GUI is considered as the essential factor for performance enhancement in this field.

Bremen Speller is one of the earliest high-speed SSVEP BCI spellers contributed by the multi-target stimulus paradigm [29]. And Jiang et al. proposed a dynamic stopping strategy for improving the performance of high-speed BCI speller [30]. Moreover, multi-phase SSVEP spellers are utilised by a low number of distinct stimuli [31]. This category of BCI speller is used for outputting a character by several times of SSVEP recognitions in the corresponding time phases. The numerical limitation of stimulus results in a low spelling speed [32]. The reason is that multi-target one-phase SSVEP speller is unfriendly for users. Much more flashing stimulus are not comfortable for subjects. On the other hand, mental workloads of control tasks are too unsustainable to control this system efficiently for subjects. Hence, multi-phase SSVEP spelling systems may be convenient for BCI control.

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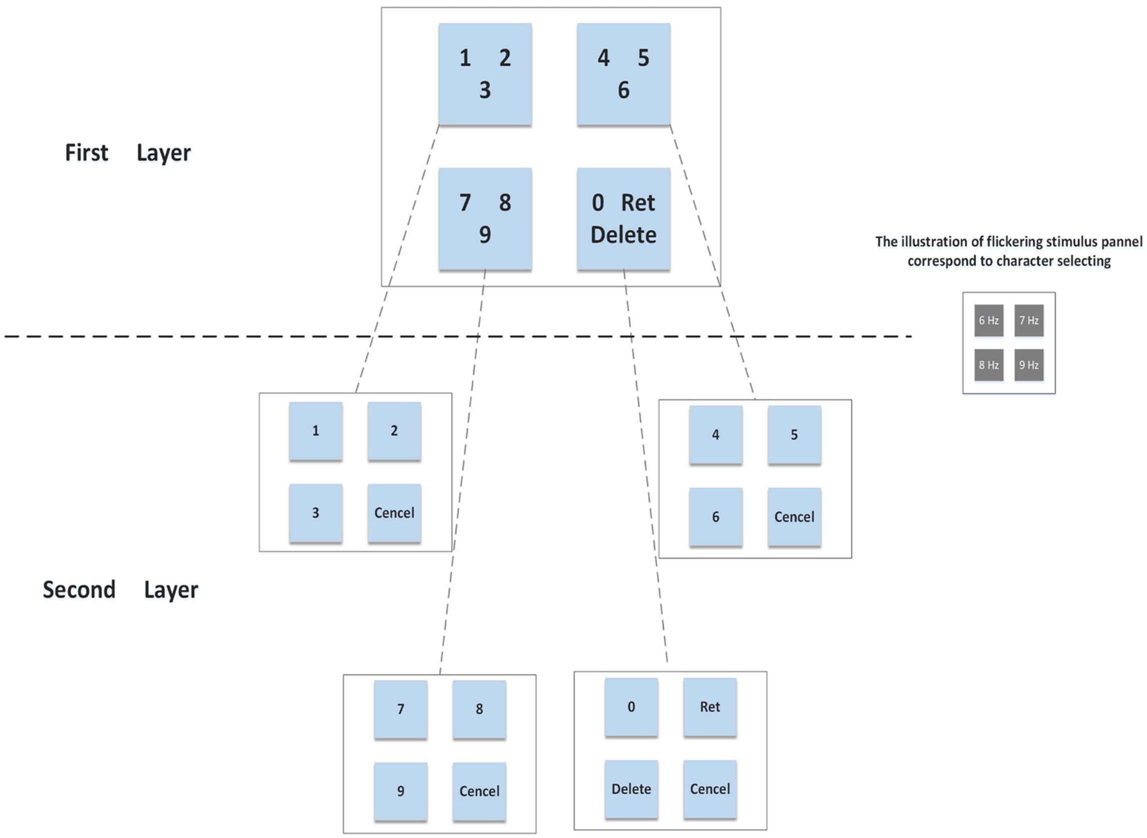

FIGURE 1. Two-layer speller was designated for character input. The subject could select the associating character by gazing corresponding flickering square layer by layer.

In this study, we proposed a novel real-time SSVEP-based BCI system for character input. Previously, a sliding control protocol had been used for improving the efficiency of robotic devices [33], [34]. It was confirmed that sliding control is widely applied for mechanical control owing to manipulation effort. As well, it was demonstrated that the sliding control protocol raised the classification accuracy of SSVEP recognition [35]. Consequently, our study aimed to develop the safety and feasibility of online multi-phase BCI system for character input with a sliding control protocol.

II. MATERIALS AND METHODS

A. SYSTEM PARADIGM OF REAL-TIME BCI

In this paper, a two-layer interface of characters selection was proposed for numerical input (Fig. 1). There were four stimulus square areas flickered within different fixed frequencies in a layer. 10 digits and 3 symbols (“1”, “2”, “3”, “4”, “5”, “6”, “7”, “8”, “9”, “0”, “Cancel”, “Ret”, “Delete”) were divided into four square areas in the first layer. After the user targeted one certain area, one of four target characters could be hit in the second layer. Except for ten numbers, “Ret” was used for returning former layer when the subject made a mistake in the first selection. “Cancel” was used for cancelling the former input digit. And “Delete” was designed for cleaning all input numbers. These buttons were applied to correct false manipulations. In a run, four flashing-block stimulus were used for presenting flickering squares at four frequencies. It was verified that the bandwidth 6-16 Hz was most effective for SSVEP recognition [36]. In order to reduce experimental fatigue and increase the discriminability of neighboring target frequencies, four low frequencies (i.e. 6, 7, 8, 9 Hz) were selected as the fundamental parameters for stimulus presentation. The target square was selected by gazing the corresponding flashing block. The monitor resolution is 1,280×768 pixels.

B. SLIDING CONTROL PROTOCOL OF EEG SIGNAL RECOGNITION

In the previous study, we had proposed a high-efficiency sequence detection (SD)-based approach for off-line SSVEP signals recognition. SD approach was composed of sequential decisions from sliding observation periods. This method could be used for the online SSVEP recognition by sequential signal collection. The control protocols were illustrated in Fig. 2 for comparison. When the subject launched the system, EEG data were acquired for signal processing. The target frequencies were selected by the control strategy for commands output. We used traditional CCA and improved SD-CCA methods for performing the real-time BCI task of character inputting. CCA method was a

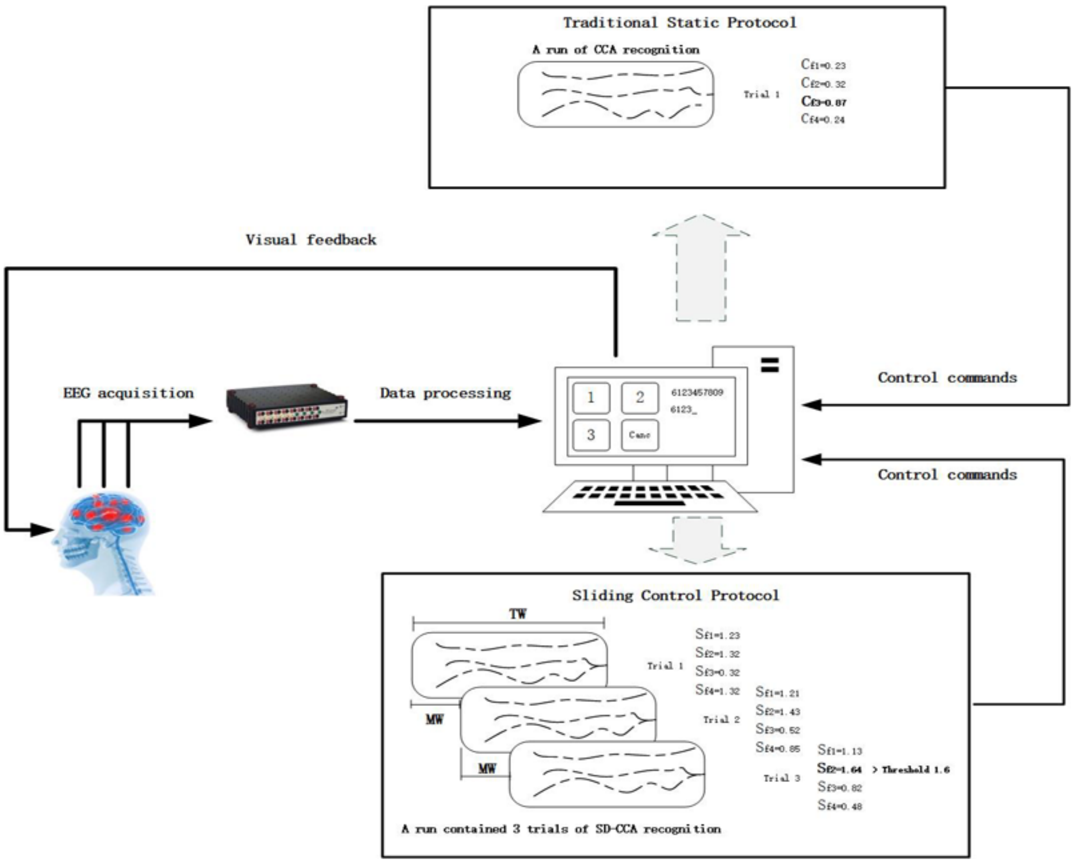

FIGURE 2. The control protocol of BCI speller for two strategies. In our method, EEG data were separated by a TW, and it was slid with an MW between consecutive trials.

common algorithm for SSVEP-based BCI tasks. For SD approach, a time window (TW) was applied to extract EEG data of one trial and a moving window (MW) was slid for consecutive trials sequentially. In a trial, canonical correlation analysis (CCA) coefficients were calculated by our algorithm. And the target was hit after performing several trials according to a threshold strategy. A detailed description of our methodology had been clarified in the section of SD Analysis Based on CCA. Parameters of TWs, MWs and thresholds were selected by the off-line experimental results for all participants. For traditional CCA method, the target was recognised by the SSVEP signal processing every time window of static 3 seconds.

C. SD ANALYSIS BASED ON CCA

Instantaneous probability, which represented the probability for the frequency of the corresponding SSVEP component, was recognised at the instantaneous period. And we used CCA coefficients to reflect the instantaneous probability in this algorithm. CCA was a typical multi-variable correlation technique for two sets of data. The hypothesis of this means was that the signal source for SSVEP, Y, was the output of a linear system with the observed signal, X, as the input. X, at a specified target frequency F could be decomposed into the Fourier series of its harmonic signals $(\sin(2\pi ft), \cos(2\pi ft), \sin(4\pi ft), \ldots)$:

$$X = \begin{cases} \sin(2\pi ft) \\ \cos(2\pi ft) \\ \sin(4\pi ft) \\ \cos(4\pi ft) \\ \sin(6\pi ft) \\ \cos(6\pi ft) \end{cases} \qquad t = \frac{1}{S}, \frac{2}{S}, \cdots, \frac{T}{S} \tag{1}$$

where f was a fundamental frequency, T was multi-channel sampling variables and S was a sampling rate. The method could detect a pair of linear combinations, $y = Y^T W_Y$ and $x = X^T W_X$, for Y and X, to maximise the dependency between two canonical variables, y and x, by solving the optimisation problem:

$$\begin{aligned} \max_{W_X, W_Y} \rho(x, y) &= \frac{E[x^T y]}{\sqrt{E[x^T x]E[y^T y]}} \\ &= \frac{E[W_X^T X Y^T W_Y]}{\sqrt{E[W_X^T X X^T W_X]E[W_Y^T Y Y^T W_Y]}} \end{aligned} \tag{2}$$

The canonical correlation coefficient ρ was used as the coefficient which represented the relation between the raw signals and the reference signals.

In a run of task recognition, EEG data were divided into several subsequent trials for evaluating instantaneous probabilities. Fig. 2 had illustrated the principle of data segmentation. A time window (TW) was used for acquiring enough multi-channel data, and it was slid with a moving window (MW) between consecutive trials. In a trial, we calculated the instantaneous probability ratio Pb_i of the stimulus frequency i as below,

$$Pb_i = \frac{\rho_i}{Mi} \tag{3}$$

where Mi was defined as

$$Mi = \frac{\sum_n \rho_j}{n} \quad j = 1, 2, \ldots, n \tag{4}$$

Here, n represented the number of stimulus frequencies. After m trials, SD coefficient S_F^m, which denoted a probability ratio of one stimulus frequency F, could be formulated as

$$S_F^m = Pb_F^1 \times Pb_F^2 \times \cdots \times Pb_F^{m-1} \tag{5}$$

A threshold of SD, T, was utilised for the final decision. If $S_F^m \geq T$, the stimulus frequency F was selected as the target frequency. If $S_F^m < T$, SD continued to assess the point of S_F^{m+1} in the next trial. In this study, TWs and MWs were respectively set by subjects' experimental performances.

The core of SSVEP recognition was how to determine the deadline point when the mental activities stayed in the steady state. Suppose that K stimulus frequencies $F_1, F_2, \ldots, F_K$ were designated for evoking relevant potentials and EEG data had been collected from N channels within a time window of L s. In this strategy, stimulus frequency F_s, corresponding to one specified flickering module concerned by one subject, must satisfy

$$F_s = \max_F S(F) \quad S(F) > T, F = F_1, F_2, \ldots, F_K \tag{6}$$

where $S(F)$ was the SD coefficients. X and Y were defined in (1). In the online experiment, the character would be outputted if F_s the threshold was exceeded. The target frequency was selected by the current maximum value of S_F^m.

D. EVALUATION METHODS

In this study, classification accuracy was applied to evaluate the experimental performance. Only right runs of selecting target numbers were valid for character input. The classification accuracy was defined as the percentage of valid runs in which classification results were consistent with target characters. Let F_s be the classification result determined by the recognising method and F_{stim} be the target frequency of a run. Thus, the classification accuracy could be formulated as follows.

$$Acc = \frac{\text{number of valid runs}(F_s = F_{stim})}{\text{number of runs}} \times 100\% \tag{7}$$

Information transfer rate (ITR) was conventionally used for assessing the communication capacity of our BCI system. This indicator was represented by the information transmitted within bits per minute. The definition of ITR (B_r) was described as:

$$B_r = \frac{60}{S} \times \left[\log_2 N + P \times \log_2 P + (1-P) \times \log_2\left(\frac{1-P}{N-1}\right)\right] \tag{8}$$

S was calculated as the mean time of character input. In our experiment, the final character was outputted by two trials for two-layer paradigm design. Hence, for traditional static protocol, the value was 6 seconds (the time consumption of one trial was 3 seconds). Moreover, the output speed was determined by the real time consumption of all runs for sliding control protocol. The detailed values were listed in the section of Result. N indicated the number of target choices which equals to 16 in online experiments (4 × 4 character choices) and P denoted the correct probability of character selection.

E. SUBJECTS AND EXPERIMENTAL SETTINGS

10 of 14 subjects who performed best off-line experimental performances (9 males and 1 female, aged from 22 to 28, mean age 24.6 years) participated in further real-time BCI tasks. All of them had normal or corrected-to-normal vision. These subjects had no experience on the online SSVEP-based BCI tasks. They were divided into two groups with an equal number. Every participant was randomly selected to one of two groups. Sliding control protocol (SCP) was used for data process in one group, and traditional static protocol (TSP) was used for the other. Each subject was asked to seat in an armchair and pay attention to the computer screen. After a cross arrow appeared 5 seconds, 10 fixed numbers (from 0 to 9) were displayed in a random order. It was fair for two control groups by maintaining the consistent task difficulty.

All subjects performed this BCI task of real-time numerical input. A high-performance amplifier (g.Tec) was used for collecting scalp EEG signals. SSVEPs were typically related to the neural activities on the visual cortex. Therefore, the record electrodes of four channels (POz, O1, Oz, O2) were placed on the occipital area according to the standard 10-20 international system (Fig. 3). Reference electrode was on the unilateral (left or right) ear lobe and a ground electrode was placed on the anterior head. Impedances of all electrodes were kept below 10 kΩ and the sample rate was 256 Hz. The signal was preprocessed by notch filtering with 50 Hz and bandpass filtering between 0.1 and 30 Hz. The same parameters (TSP: TW = 3 s; SCP: TW = 3 s, MW = 0.6 s) were determined by the off-line experiments for eliminating subject-dependent difference. However, the performances with these parameters were excellent for all subjects in the off-line tasks, especially for ITR. Moreover, the time delay of software would influence the performance of experimental result. We made a record of total task time ($Time_{total}$) from start to end for each subject by programming. Thus, the average time consumption per trial could be calculated as

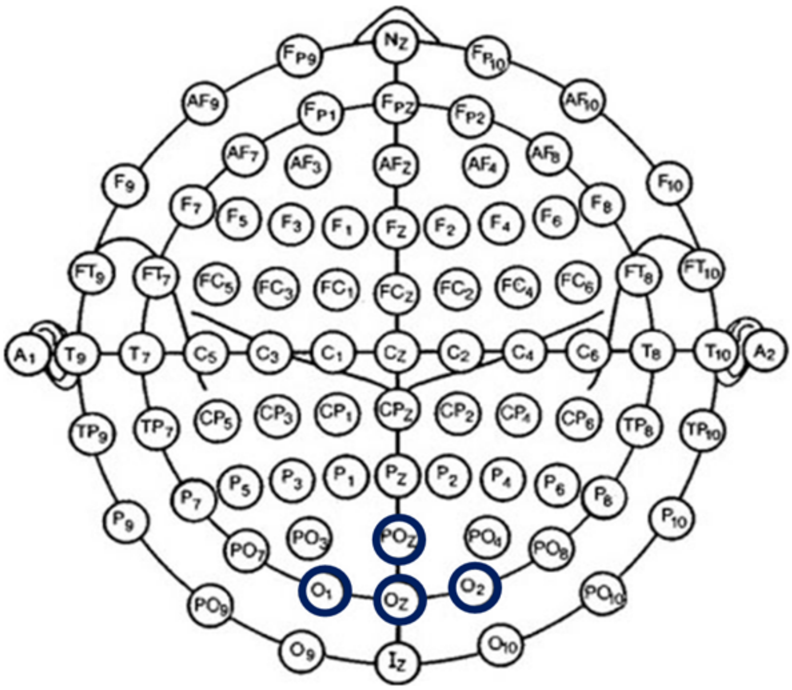

FIGURE 3. The record electrodes of four channels (POz, O1, Oz, O2) were placed on the standard 10-20 international system.

TABLE 1. The comparable results between TSP and SCP, including ACC, ITR and time consumption per trial.

Group	SCP						TSP					
Subject	2	3	4	8	9	**Mean value**	1	5	6	7	10	**Mean value**
ACC (%)	91.0	83.3	76.9	100	100	90.3	76.9	76.9	62.5	76.9	66.7	72.0
ITR (bits/min)	23.22	19.13	15.95	29.27	29.70	23.45	22.80	22.38	15.20	21.53	17.35	19.85
Time Consumption per trial(seconds)	4.15	4.23	4.36	4.10	4.04	4.18	3.05	3.11	3.12	3.23	3.08	3.12

TABLE 2. The detailed process of character inputs for all subjects.

Group	SCP		TSP	
	Sub 2	Cancel-6-3-7-8-5-1-2-4-9-0	Sub 1	7-4-Ret-4-8-2-Cancel-6-0-9-3-1-5
	Sub 3	2-0-7-Ret-8-9-1-5-7-6-3-4	Sub 5	6-2-Ret-1-9-4-Cancel-0-3-8-7-2-5
	Sub 4	5-Cancel-2-1-7-6-7-Ret-8-9-0-3-4	Sub 6	9-2-Del-9-1-Ret-2-1-6-0-8-3-7-Cancel-4-5
	Sub 8	5-4-0-1-8-6-9-3-2-7	Sub 7	1-5-7-3-Cancel-4-Cancel-6-8-9-Cancel-0-2
	Sub 9	8-9-2-0-3-7-4-1-5-6	Sub 10	Cancel-9-2-6-Cancel-5-3-Ret-3-0-1-7-Cancel-6-4-8

$Time_{total}/Number_{trials}$. $Number_{trials}$ was the number of all trials, and it was meaningful for computing the evaluation indicator exactly.

III. RESULTS

A. SYSTEMATICAL PERFORMANCE FOR TWO GROUPS

Table 1 showed the comparison results of these two groups. The results of paired t-test (ACC: $t = 2.476, p < 0.05$; ITR: $t = 1.278, p > 0.05$) verified the significant improvement of classification accuracy for SCP. Though the average time consumption of SCP was higher than that of TSP, the mean ITR of SCP was larger than that of TSP. It was indicated that the longer time of data collecting was useful for improving the efficiency of the online BCI system. These findings validated the efficiency of SCP strategy for online BCI tasks.

B. MANIPULATION CONTROL FOR ON-LINE BCI

The detailed process of character inputs was reported at Table 2. Generally, the number of error manipulations for SCP was lower than that of TSP. This result was consistent with the conclusion of off-line sliding control strategy [35]. The observation of sequence segmentation was beneficial against instantaneous mental disturbance. It was validated that sliding control was feasible for on-line BCI tasks.

IV. DISCUSSION

The main findings of this study imply that SCP enabled high-efficiency and precise BCI system for character input. The control strategy strengthens the robustness of online BCI spellers. With the development of hardware technology, it will be useful for real applications in future.

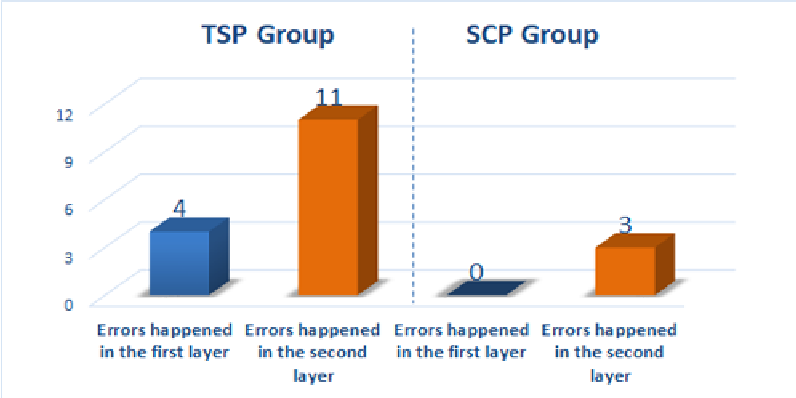

FIGURE 4. **The number of manipulation errors in the first layer and the second layer of GUI for TSP group.**

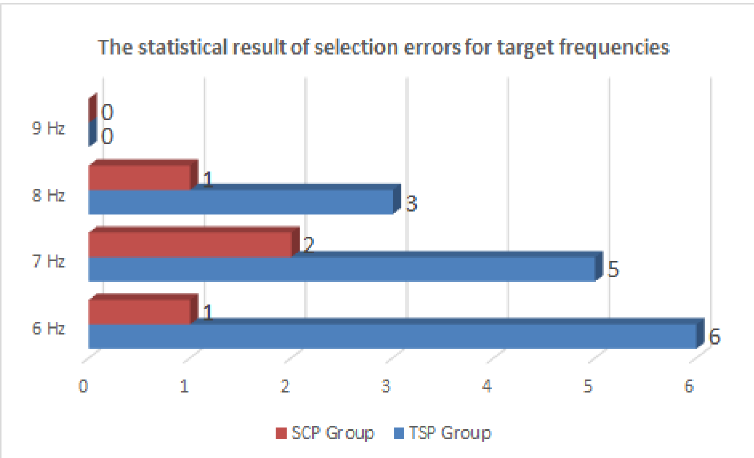

FIGURE 5. **The number of selection errors of target frequencies (6 HZ, 7 Hz, 8 Hz, 9 Hz) for TSP group.**

Conventionally, the number of stimulus and time consumption were considered as the main factors of improving the efficiency of BCI spellers [21], [37]. However, the complexity of systematical control was almost not mentioned in previous studies. Comparing with state-of-art multi-phase BCI spellers, the performance of our BCI system reaches the same level with those of them [31], [32], [38]. Our system adopts SCP for eliminating mental interference. It enhances positive experiences due to the least error happened in control. In the previous task, we used more collected time for SSVEP recognition to verify the feasibility of the proposed method. Moreover, the number of target choices was added to 16 in the online experiments. The reduction of time consumption and the increasement of target choices were adopted to improve the efficiency of real-time BCI system. Hence, the average ITR of the off-line task was significantly lower than of the online task.

In this experiment, subjects performed the online character spelling task by two control protocols. subjects in the group of SCP had lower false manipulation than that of subjects in the group of TSP. We report the numbers of manipulation errors in the first and second layers in Fig. 4. Firstly, gaze shifting is considered as an influential factor when the visual focus diverts from one target to another between two consecutive trials. In contrast with SCP, these operation errors indicated that visual deflection has an impact on experimental results. Moreover, selection errors of target frequencies are listed in Fig. 5 for evaluating these strategies. It is shown that the targets (i.e., 6 Hz and 7 Hz) selections in the top of the interface are more difficult than thus in the bottom. We speculate that it is related to the visual range of the user interface. The details will be revealed in the next paragraph. Generally, TSP is challenging to eliminate external interference.

For instance, Fig. 6 shows the process of target evaluation. The interference stimuli (i.e., 8 Hz) is selected at the first three trials. Although, target selection is not performed because the coefficient is lower than the threshold in the process. In the subsequent trials, the score of right stimuli (i.e., 6 Hz) surpassed that of the interference stimuli. It is clearly demonstrated that SCP improves the robustness of the SSVEP-BCI speller against mental interference.

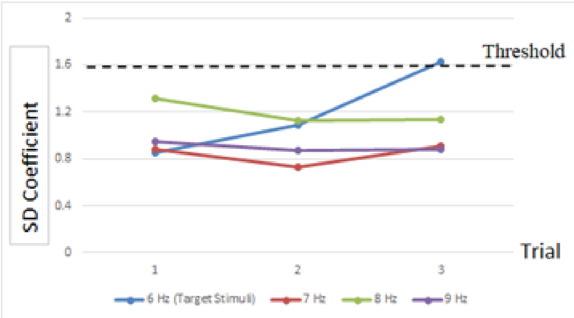

FIGURE 6. The chart illustrates the process of SD coefficients at stimulus frequencies for Subject 9. In the first two trials, The SD coefficients of target frequency (i.e. 6 Hz) are less than those of the interference frequency (i.e. 8 Hz) However, it surpasses that of the interference frequency at subsequent two trials and the threshold is hit at the last trial.

In our experiment, the time consumption per trial is ranged from 4.04 to 4.36 seconds for SCP. It is implied that the subject spends more time in performing one recognition of SSVEP signal. Comparatively, the recognising time window of TSP is set to three seconds for one recognition, which is dependent on the off-line task result. These parameters were reasonable for the comparison between these two control protocols.

For SCP group, they gave positive feedback to the manipulation experience for their online BCI experiments. However, it was difficult for TSP group to make a correct selection by the subjects' experiences. It was implied that the subjective confidence was raised in the condition of few false operations. Furthermore, none of participants gave negative responses for real-time missions. The conclusion proves that, SCP is acceptable for online BCI system.

As introduced, four channels are used for signal acquiring. It is suitable for the real application with dry-electrodes. It is confirmed that this device will be exploited for commercial applications in future.

In our study, the brain-switch is not used in our system. However, it is helpful for safety control in the field of mechanical engineering. In the further work, we will designate it in our BCI speller for self-paced control.

V. CONCLUSION

In this paper, we presented a novel SSVEP-based BCI system with sliding control protocol. These findings validated the high-efficiency of our proposed BCI speller. And the comparison result with the static control protocol verified that the superiority of sliding control strategy for real-time tasks.

REFERENCES

[1] G. Pfurtscheller, G. R. Müller-Putz, A. Schlogl, B. Graimann, R. Scherer, R. Leeb, C. Brunner, C. Keinrath, F. Lee, G. Townsend, C. Vidaurre, and C. Neuper, "15 years of BCI research at Graz university of technology: Current projects," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 205–210, Jun. 2006.

[2] C. Neuper, G. Müller-Putz, R. Scherer, and G. Pfurtscheller, "Motor imagery and EEG-based control of spelling devices and neuroprostheses," *Prog. Brain Res.*, vol. 159, no. 10, pp. 393–409, 2006.

[3] N. Birbaumer, "Breaking the silence: Brain-computer interfaces (BCI) for communication and motor control," *Psychophysiology*, vol. 43, no. 6, pp. 517–532, 2006.

[4] C. Guger, S. Daban, E. Sellers, C. Holzner, G. Krausz, R. Carabalona, F. Gramatica, and G. Edlinger, "How many people are able to control a P300-based brain–computer interface (BCI)?" *Neurosci. Lett.*, vol. 462, no. 1, pp. 94–98, 2009.

[5] A. Rezeika, M. Benda, P. Stawicki, F. Gembler, A. Saboor, and I. Volosyak, "Brain computer interface spellers: A review," *Brain Sci.*, vol. 8, no. 4, p. 57, 2018.

[6] J. Jin, E. Sellers, S. Zhou, Y. Zhang, and X. Wang, "A P300 brain–computer interface based on a modification of the mismatch negativity paradigm," *Int. J. Neural Syst.*, vol. 25, no. 3, 2015, Art. no. 1550011.

[7] D. J. Krusienski, E. W. Sellers, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, "Toward enhanced P300 speller performance," *J. Neurosci. Methods*, vol. 167, no. 1, pp. 15–21, Jan. 2008.

[8] I. Käthner, A. Kübler, and S. Halder, "Rapid P300 brain-computer interface communication with a head-mounted display," *Frontiers Neurosci.*, vol. 9, p. 207, Jun. 2015.

[9] J. Jin, E. W. Sellers, and X. Wang, "Targeting an efficient target-to-target interval for P300 speller brain–computer interfaces," *Med. Biol. Eng. Comput.*, vol. 50, pp. 289–296, Mar. 2012.

[10] W. Speier, C. Arnold, and N. Pouratian, "Integrating language models into classifiers for BCI communication: A review," *J. Neural Eng.*, vol. 13, May 2016, Art. no. 031002.

[11] F. Akram, S. M. Han, and T.-S. Kim, "An efficient word typing P300-BCI system using a modified T9 interface and random forest classifier," *Comput. Biol. Med.*, vol. 56, pp. 30–36, Jan. 2015.

[12] Z. Lin, C. Zhang, Y. Zeng, L. Tong, and B. Yan, "A novel P300 BCI speller based on the triple RSVP paradigm," *Sci. Rep.*, vol. 8, no. 1, p. 3350, 2018.

[13] B. Blankertz, G. Dornhege M. Krauledat, M. Schröder, J. Williamson, R. Murray-Smith, and K.-R. Müller, "The Berlin brain-computer interface presents the novel mental typewriter Hex-o-Spell," in *Proc. 3rd Int. Brain-Comput. Interface Workshop Training Course*, 2006, pp. 108–109.

[14] J. Yue, J. Jiang, Z. Zhou, and D. Hu, "SMR-speller: A novel brain-computer interface spell paradigm," in *Proc. 3rd Int. Conf. Comput. Res. Develop.*, Mar. 2011, pp. 187–190.

[15] L. Cao, B. Xia, O. Maysam, J. Li, H. Xie, and N. Birbaumer, "A synchronous motor imagery based neural physiological paradigm for brain computer interface speller," *Frontiers Hum. Neurosci.*, vol. 11, p. 274, May 2017.

[16] S. Perdikis, R. Leeb, and J. D. R. Millán, "Context-aware adaptive spelling in motor imagery BCI," *J. Neural Eng.*, vol. 13, 2016, Art. no. 036018.

[17] T. D'albis, R. Blatt, R. Tedesco, L. Sbattella, and M. Matteucci, "A predictive speller controlled by a brain-computer interface based on motor imagery," *ACM Trans. Comput.-Hum. Interact.*, vol. 19, no. 3, p. 20, 2012.

[18] I. Volosyak, F. Gembler, and P. Stawicki, "Age-related differences in SSVEP-based BCI performance," *Neurocomputing*, vol. 250, pp. 57–64, Aug. 2017.

[19] I. A. Ansari and R. Singla, "BCI: An optimised speller using SSVEP," *Int. J. Biomed. Eng. Technol.*, vol. 22, no. 1, pp. 31–46, 2016.

[20] Q. Wei, H. Gong, and Z. Lu, "Grouping modulation with different codes for improving performance in CVEP-based brain–computer interfaces," *Electron. Lett.*, vol. 53, pp. 214–216, Feb. 2017.

[21] X. Chen, Y. Wang, M. Nakanishi, X. Gao, T. Jung, and S. Gao, "High-speed spelling with a noninvasive brain–computer interface," *Proc. Nat. Acad. Sci. USA*, vol. 112, no. 44, pp. 6058–6067, 2015.

[22] M. Nakanishi, Y. Wang, X. Chen, Y. Wang, X. Gao, and T.-P. Jung, "Enhancing detection of SSVEPs for a high-speed brain speller using task-related component analysis," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 1, pp. 104–112, Jan. 2018.

[23] O. Friman, I. Volosyak, and A. Graser, "Multiple channel detection of steady-state visual evoked potentials for brain-computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 4, pp. 742–750, Apr. 2007.

[24] S. Parini, L. Maggi, A. C. Turconi, and G. Andreoni, "A robust and self-paced BCI system based on a four class SSVEP paradigm: Algorithms and protocols for a high-transfer-rate direct brain communication," *Comput. Intell. Neurosci.*, vol. 2009, Feb. 2009, Art. no. 864564.

[25] C. Guger, B. Z. Allison, B. Growindhager, R. Prückl, C. Hintermüller, C. Kapeller, M. Bruckner, G. Krausz, and G. Edlinger, "How many people could use an SSVEP BCI?" *Frontiers Neurosci.*, vol. 6, p. 165, 2012.

[26] Y. Zhang, E. Yin, F. Li, Y. Zhang, T. Tanaka, Q. Zhao, Y. Cui, P. Xu, D. Yao, and D. Guo, "Two-stage frequency recognition method based on correlated component analysis for SSVEP-based BCI," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 7, pp. 1314–1323, Jul. 2018.

[27] B. Allison, T. Lüth, D. Valbuena, A. Teymourian, I. Volosyak, and A. Gräser, "BCI demographics: How many (and what kinds of) people can use an SSVEP BCI?" *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 2, pp. 107–116, Apr. 2010.

[28] E. Yin, Z. Zhou, J. Jiang, Y. Yu, and D. Hu, "A dynamically optimized SSVEP brain–computer interface (BCI) speller," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 6, pp. 1447–1456, Jun. 2015.

[29] I. Volosyak, "SSVEP-based Bremen-BCI interface–boosting information transfer rates," *J. Neural Eng.*, vol. 8, May 2011, Art. no. 036020.

[30] J. Jiang, E. Yin, C. Wang, M. Xu, and D. Ming, "Incorporation of dynamic stopping strategy into the high-speed SSVEP-based BCIs," *J. Neural Eng.*, vol. 15, no. 4, 2018, Art. no. 046025.

[31] C. Kick and I. Volosyak, "Evaluation of different spelling layouts for SSVEP based BCIs," in *Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2014, pp. 1634–1637.

[32] Y. Wang, Y.-T. Wang, and T.-P. Jung, "Visual stimulus design for high-rate SSVEP BCI," *Electron. Lett.*, vol. 46, no. 15, pp. 1057–1058, Jul. 2010.

[33] A. R. Kim and Y.-S. Lee, "Application of sliding rehabilitation machine in patients with severe cognitive dysfunction after stroke," *Appl. Sci.*, vol. 9, no. 5, p. 927, 2019.

[34] X. Xia, X. Ma, and J. Wang, "Control method for signalized intersection with integrated waiting area," *Appl. Sci.*, vol. 9, no. 5, p. 968, 2019.

[35] L. Cao, Z. Ju, J. Li, R. Jian, and C. Jiang, "Sequence detection analysis based on canonical correlation for steady-state visual evoked potential brain computer interfaces," *J. Neurosci. Methods*, vol. 253, pp. 10–17, Sep. 2015.

[36] X. Gao, D. Xu, M. Cheng, and S. Gao, "A BCI-based environmental controller for the motion-disabled," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 137–140, Jun. 2003.

[37] H. Cecotti, "A self-paced and calibration-less SSVEP-based brain–computer interface speller," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 2, pp. 127–133, Apr. 2010.

[38] T.-H. Nguyen, D.-L. Yang, and W.-Y. Chung, "A high-rate BCI speller based on eye-closed EEG signal," *IEEE Access*, vol. 6, pp. 33995–34003, 2018.

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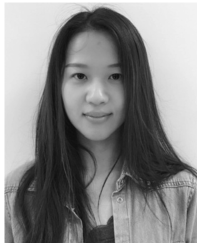

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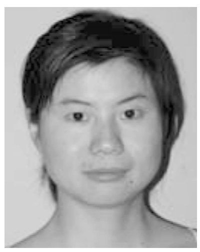

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