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Technical Note

Development of a hybrid mental spelling system combining SSVEP-based brain–computer interface and webcam-based eye tracking

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ABSTRACT

The goal of this study was to develop a hybrid mental speller that can effectively prevent unexpected typing errors in the steady-state visual evoked potential (SSVEP)-based mental speller by simultaneously using the information of eye-gaze direction detected by a low-cost webcam without calibration. In the implemented hybrid mental speller, a character corresponding to the strongest SSVEP response was typed only when the position of the selected character coincided with the horizontal eye-gaze direction ('left', 'no direction', or 'right') detected by the webcam-based eye tracker. When the character detected by the SSVEP-based mental speller was located in the direction opposite the eye-gaze direction, the character was not typed at all (a beep sound was generated instead), and thus the users of the speller did not need to correct the mistyped character using a 'BACKSPACE' key. To verify the feasibility and usefulness of the developed hybrid mental spelling system, we conducted online experiments with ten healthy participants, each of whom was asked to type 15 English words consisting of a total of 68 characters. As a result, 16.6 typing errors could be prevented on average, demonstrating that the proposed hybrid strategy could effectively enhance the performance of the SSVEP-based mental spelling system.

1. Introduction

Many individuals suffering from serious neurological disorders such as amyotrophic lateral sclerosis (ALS), brainstem stroke, and spinal cord injury have difficulty in communicating with other people or controlling their external environment. Brain–computer interfaces (BCIs) are non-muscular communication and interaction technologies that allow these disabled individuals to communicate with the outside world using their brain signals [1]. To date, a variety of neural signals have been used with the aim of implementing practical BCI applications, such as electroencephalography (EEG) [1–13], magnetoencephalography (MEG) [14,15], electrocorticography [16,17], near-infrared spectroscopy [18–20], functional magnetic resonance imaging [21,22], and transcranial Doppler ultrasound [23,24]. In particular, the number of EEG-based BCI applications has increased markedly during the past five years [5].

One of the most representative EEG-based BCI applications is the BCI speller, which allows paralyzed users to spell out words by simply gazing at the target characters [25–31]. So far, most mental spelling systems have been developed based on the visual P300, which is an event-related potential (ERP) component induced by irregular, infrequent, and task-relevant visual stimuli [27–30]. N200, a negative ERP component evoked by motion-onset visual stimuli [32,33], and modulation of EEG rhythmic activity due to motor imagery [34] have also been used for implementing mental spelling systems. Since these ERPs have proved to have relatively lower intra- and inter-subject variability compared to the classical motor imagery-based BCI paradigms, ERP-based spellers do not generally require long training time [27–30,32,33]. Recently, some BCI studies have reported the successful implementation of mental spelling systems based on steady-state visual evoked potential (SSVEP), which is a periodic EEG response elicited by a visual stimulus flickering or reversing at a specific frequency [25,31]. The SSVEP-based BCI systems have received increasing attention

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because they provide a high information transfer rate, require relatively few electrodes, and generally do not require any training, as compared to the requirements of other BCI systems [1,35]. In the SSVEP-based mental spelling systems, the users are supposed to gaze at one of several visual stimuli with different flickering frequencies in order to generate a target command, and the systems can select the target by detecting the changes in EEG spectral power recorded around the visual cortex. SSVEP-based BCI systems have been implemented with different design types such as a moving cursor type [31] and a multi-step decision-tree type [25], both of which needed a series of multiple commands to be generated to spell a character.

Recently, our group implemented an SSVEP-based mental spelling system adopting a QWERTY style keyboard layout with 30 light-emitting diodes (LEDs) flickering at different frequencies with a 0.1-Hz inter-frequency span [26]. Because the number of visual stimuli was identical to that of the target characters, users could spell a target character directly in a single trial. Our previous system showed high performance (letters per minute = 9.39) in online experiments. However, characters that were located in the direction opposite the users' gaze were frequently mistyped, because thirty stimulation frequencies were assigned to each key in such a way that each frequency was allocated sequentially as far from those assigned to its neighboring LEDs as possible in order to minimize the false positives caused by peripheral vision. In the cases of the mistyping, the users needed to spend additional time to correct the typing error using a 'BACKSPACE' key.

The goal of the present study was to enhance the performance of the mental spelling system by preventing predictable typing errors (typos) in advance. To this end, we combined the previous mental speller with a low-cost webcam-based eye tracker that can accurately estimate horizontal eye-gaze directions ('left' or 'right') without any pre-calibration processes. In order to confirm the feasibility of our hybrid mental spelling system, online experiments were conducted with 10 participants. The basic concept of the proposed error prevention method is similar to that of the error-related potential (ErrP)-based error detection method [36–41]; however, unlike the ErrP-based method, the proposed hybrid mental speller detects typing errors before visualizing the mistyped characters, which will be discussed further in Section 4.

2. Methods

2.1. An SSVEP-based mental spelling system with 30 flickering LEDs

In the previously implemented mental spelling system, a modified QWERTY keyboard layout consisting of 30 LED keys was introduced, as shown in Fig. 1(A). Twenty-six keys were assigned to each of the English alphabet letters and the other four keys were assigned to four symbols, which represented 'BACKSPACE', 'ENTER', 'PUNCTUATION', and 'SPACE'. The size of each key except the 'ENTER' and 'SPACE' keys was set to 2 cm × 2 cm, and the distances between neighboring keys were set to 2.5 cm both horizontally and vertically.

The 30 LEDs flickering with different frequencies were attached to the back of thirty key slots, and the frequencies were evenly divided within the frequency band of 5.0–7.9 Hz with a span of 0.1 Hz [26]. Lastly, the selected stimulation frequencies were assigned to each key, with each frequency allocated sequentially to be as far from those assigned to its neighboring LEDs as possible. The minimum frequency difference between adjacent keys was set to be 0.7 Hz. This frequency difference was thought to be large enough to discriminate adjacent keys, considering even smaller frequency difference (0.195 Hz) was successfully used for

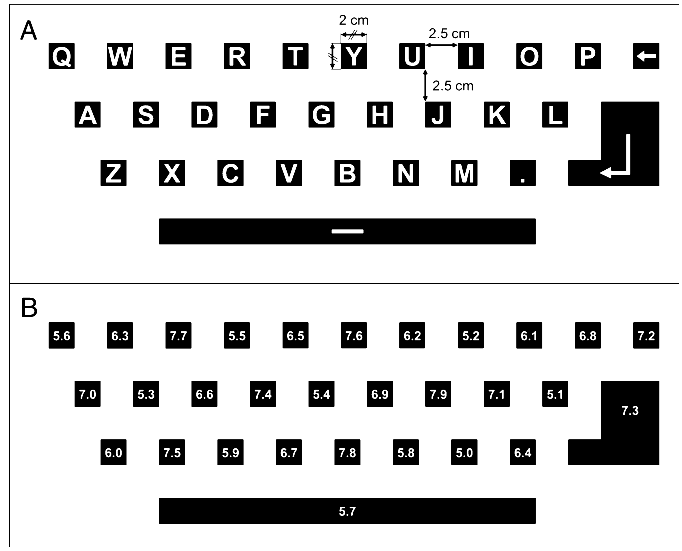

Fig. 1. The modified QWERTY keyboard layout and an example of the stimulation frequency arrangement. (A) Twenty-six keys were used for the letters of the English alphabet, and the other four keys were used for special symbols representing BACKSPACE, ENTER, PUNCTUATION, and SPACE. (B) An example of the stimulation frequency arrangements generated assuming 30 frequencies ranging from 5.0 Hz to 7.9 Hz with a span of 0.1 Hz.

implementing an SSVEP-based BCI application (i.e., TV remote controller) [42]. Fig. 1(B) shows an example of the stimulation frequency arrangements.

In order to spell a character, the users were supposed to gaze at the target character for a predetermined time period (e.g., 3 s). For the determination of the character that a user was gazing at, we used a simple classification algorithm, which found the frequency with the largest SSVEP response. In case of errors, the user could correct a misspelled character using the 'BACKSPACE' key. Video of the online experiments performed with the previous mental spelling system can be found in the following YouTube link: http://www.youtube.com/watch?v=uunf3FDfEno

2.2. Webcam-based eye-tracking

We used a commercial low-cost web-cam (Part Number 7795PC; Cosy Inc., Busan, Korea; operating current: 500 mA; range of focal point: 3 cm – ∞; 30 frames/s; maximum 30 megapixel resolution; image sensor: CMOS), of which the price was less than US $100. The web-cam-based eye-tracker estimates an eye-gaze direction of a human subject based on a template-matching method, which is widely used in the field of computer vision and is available in the OpenCV library (http://opencv.org). Let I be an input image from the web-camera, and let T_d be a template image for an eye-gaze direction. The template-matching method computes a cost function between T_d and the partial images of I for any location (x, y) as follows by using the normalized sum of squared differences of pixel intensity values:

$$C_d(x, y) = \frac{\sum_{i,j}[I(x+i, y+j) - T_d(i, j)]^2}{\sqrt{I(x+i, y+j)^2 \cdot T_d(i, j)^2}}. \quad (1)$$

The cost function is calculated at all possible positions of the template over the input image, and the position with the lowest cost is selected as the best position. The matching criterion for the set of template images, $T = \{T1, T2, \ldots\}$, is as follows:

$$\hat{d} = arg\,\min_d \min_{x,y} C_d(x, y), \quad (2)$$

where $\hat{d}$ means the index of the best-matched template.

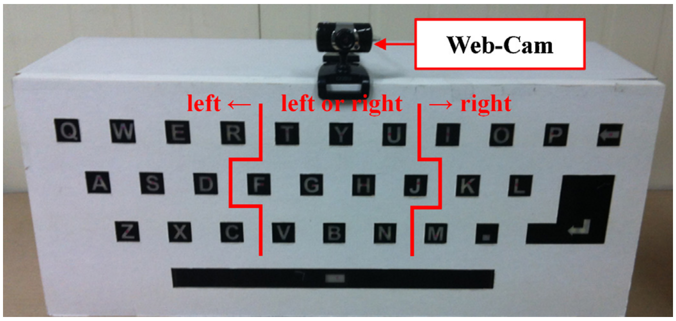

Fig. 2. An implemented hybrid mental spelling system and the criterion of the gaze direction.

In this paper, we used two types of template images for each eye-gaze direction ('left' or 'right'), and each of them was acquired in advance of the experiments. The head position of a subject was not changed severely during the experiments due to a chin rest, but the direction of eye gaze was changed according to the position of the character that the subject wants to type. We therefore created a simple rectangular binary mask around the eye-position which is similar to that used in [43], and applied it to the input image before carrying out matching with the acquired eye-templates. Through this pre-processing, we can drastically reduce the computation time in template-matching and also can obtain better estimation of eye-gaze direction.

2.3. A proposed hybrid mental spelling system

The direction of 10 characters (Q, W, E, R, A, S, D, Z, X, and C) was defined as 'left', and the direction of 9 characters (I, O, P, BACKSPACE, K, L, ENTER, M, and PUNCTUATION) was defined as 'right'. The direction of the other 11 characters (T, Y, U, F, G, H, J, V, B, N, and SPACE) was defined as 'no specific direction' (see Fig. 2). When the visual angle was set to 40°, the webcam-based eye tracker could correctly discriminate the 'left'-sided characters from the 'right'-sided characters with 100% accuracy without requiring any pre-calibration processes.

The proposed hybrid mental spelling system operated as follows. While a user was gazing at a target character flickering at a certain frequency, the SSVEP responses (spectral powers) of the recorded EEG data were estimated and used as the feature vectors. The target character that the user was gazing at was identified using a simple classification algorithm, which simply found the frequency with the largest SSVEP response. The main difference between the conventional speller and the proposed hybrid speller was that the character corresponding to the strongest SSVEP response was typed only when the position of the character coincided with the gaze direction detected by the eye tracker. Otherwise, the character was not typed at all, and a pure-tone beep sound was generated instead. Therefore, the user did not have to spend time correcting the potential typing error using the 'BACKSPACE' key. This "typo-preventing" strategy was not applied to the 11 characters located in the center of the keyboard, which were previously defined as "no specific direction" characters (see Fig. 2).

2.4. Participants and experimental conditions

Ten healthy participants (seven males and three females, 22–28 years old) participated in this study to evaluate the performance of the hybrid mental spelling system. All participants had normal or corrected to normal vision and none had a previous history of neurological, psychiatric or other severe diseases that might otherwise affect the experimental results. Before the experiment, we gave a detailed summary of the experimental procedures to each participant and received written consent from all participants. After the experiment, we provided them with monetary reimbursement for their participation. The study was reviewed and approved by the Institutional Review Board of Hanyang University, Korea.

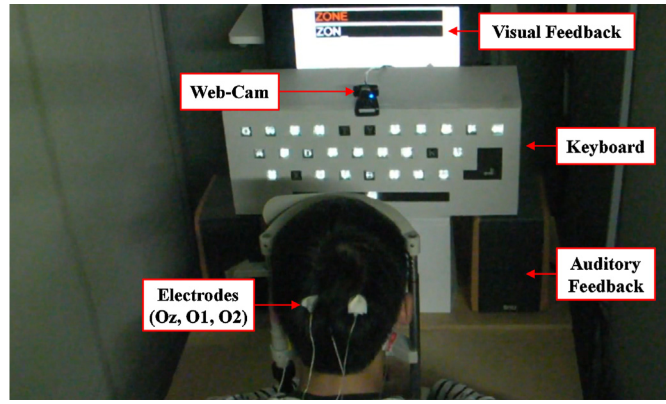

Fig. 3. A snapshot of the online experiment where a participant was trying to spell 'E' to type a given English word, 'ZONE'.

Each participant sat in a comfortable armchair in front of the hybrid mental speller, and the distance between the nasion of the participant and the hybrid mental speller was set to 44 cm (visual angle: 40°). According to the international 10–20 system, three electrodes (Oz, O1 and O2) were mounted on the occipital area of each participant's scalp. We used a multi-channel EEG acquisition system (WEEG-32, Laxtha Inc., Daejeon, Korea) to record EEG signals while each participant was concentrating on the target characters flickering at different frequencies. A reference electrode was placed at the right mastoid and a ground electrode was placed at the left mastoid. The EEG signals were sampled at 512 Hz. An anti-aliasing band pass filter with cutoff frequencies of 0.7 Hz and 50 Hz was applied. In order to prevent the misidentification of eye gaze direction due to head movement, the neck of the participant was fixed using a chin rest that was a part of an ophthalmic examination system (see Fig. 3). This experimental setting provided more realistic experimental environments, mimicking the conditions of patients with severe ALS or locked-in syndrome (LIS) who cannot communicate with others without using their brain signals, but might not be an appropriate condition for patients whose head movements are not completely abolished.

2.5. Experimental procedures

The performance of the implemented webcam-based eye tracker was confirmed by a series of preliminary experiments conducted with ten participants. The participants were asked to gaze at characters located on either the 'left' or the 'right' side for 3 s according to the verbal instructions of a researcher, and then the output of the eye tracker (either left or right) was compared with the location of the designated character. This process was repeated thirty times and the classification accuracy of the eye tracker was always 100% when the character direction was defined as in Fig. 2.

To confirm the feasibility of the hybrid mental spelling system, a series of online experiments were conducted. After the participants had some time to get accustomed to the hybrid spelling system (<3 min), they were instructed to completely spell the given 15 English words (68 characters, see Table 1). The time period required to spell one character (3–6 s) was assigned differently to each participant considering the different typing abilities of each participant evaluated in preliminary experiments [26]. The outcome was immediately presented to the participants using both visual and auditory feedback. In case of errors, the participants could correct a misspelled character using the 'BACKSPACE' key.

Table 1
The complete typing results of a single participant (P8, a male subject who showed the worst performance). In the second column of Table 1 the characters with underlining and parentheses were actual typos and prevented typos, respectively, and '←' and '_' signify the 'BACKSPACE' and 'SPACE' keys, respectively.

Target characters	Typing results	Total number of typed characters	Number of prevented typos
BABY	B(J)AB(X)Y	6	2
DESK	D(I)(N)(M)E(L)SK	8	4
GOLF	G(Z)OL(M)F	6	2
HAND	HAN$\underline{\text{T}}\underline{\text{L}}$←$\underline{\text{F}}$←←D	10	0
FACE	FAC(I)(I)(M)E	7	3
HOUR	H(Z)$\underline{\text{I}}$←OUR	7	1
TAXI	T(L)AXI	5	1
ZONE	ZO$\underline{\text{U}}$(W)←(ENTER)N(I)E	9	3
JUNE	$\underline{\text{P}}\underline{\text{\_}}\underline{\text{\_}}$←←←JUN(M)E	11	1
WATER	WAT(M)(M)E(L)R	8	3
WOMAN	W(Z)OMAN	6	1
VIDEO	VID$\underline{\text{S}}$(E)←E$\underline{\text{M}}\underline{\text{I}}$←←O	12	1
QUICK	(L)(ENTER)(L)(ENTER)QUICK	9	4
PENCIL	$\underline{\text{V}}$←PENCIL	8	0
MEMORY	M(I)(M)(M)(M)E(E)MO(L)RY	12	6
Total		124	32

If the gaze direction information obtained from the eye tracker did not coincide with the position of the character decoded from SSVEP responses, a pure tone beep sound was generated, at which time the participants were asked to gaze at the misspelled target character again. Fig. 3 shows a snap shot of the online experiment where a participant was trying to type 'E'. A sample movie of the online experiment can be found at the following URL (http://youtu.be/Ey8jxYLiUnY) or in the supplementary movie file attached to this manuscript.

3. Results

Table 1 shows the complete typing results of one participant (P8), a male subject who showed the worst performance among all of the participants, to demonstrate how the participant spelled the given 15 English words. In the second column of Table 1, the characters with underlining and parentheses represent actual typos and prevented typos, respectively, and '←' and '_' represent 'BACKSPACE' and 'SPACE', respectively. The participant entered 124 characters (including the 'BACKSPACE' key) to completely type 68 characters. The total number of typing errors was 44, but 32 typing errors were prevented by using the eye-direction information extracted from the webcam-based eye tracker. That is to say, the participant needed to correct only 12 typing errors using 'BACKSPACE' key, and thus could save at least 128 s (=32 × 4 s) in typing the 68 characters.

Table 2 summarizes the full online experimental results for all of the participants. The average number of total typing errors was 25.8, and at least 16.6 additional typing (64.34% of the number) of 'BACKSPACE' could be prevented on average by using the eye tracker information. Consequently, our hybrid mental spelling system could save at least 78.5 s for typing the given 68 characters. The time period to spell one character had a negative correlation with the "ratio of typo prevention (=the total number of typos/the number of prevented typos)" (Spearman correlation, rho = −0.6484, p = 0.0426), which suggests that our typo-prevention method might be more efficient to individuals whose typing ability is superior. The online experimental results demonstrated that the proposed hybrid mental spelling system could significantly reduce the total typing time, and thus, could significantly enhance the performance of the speller by preventing typing errors.

4. Discussion

In our online experiments, at least 16.6 additional typing of 'BACKSPACE' could be prevented, on average, by using the eye tracker information when the 10 participants typed the given 68 characters. The reason why we used "at least" in the previous sentence is that the 'BACKSPACE' key itself can also be possibly misidentified, at which time the typing of the 'BACKSPACE' key again is needed. For example, in the case of participant P8 (a male subject whose typing log is summarized in Table 1), he typed 10 characters (H A N T L ← F ← ← D) to spell 'HAND', when two letters, 'L' and 'F', were typed instead of 'BACKSPACE'. Subject P8, who showed the worst typing performance among all of the participants, generated many typing errors including the above example, but he did not have to type the 'BACKSPACE' key at all while he was writing the words 'BABY', 'DESK', 'FACE', 'GOLF', 'TAXI', 'QUICK', 'WATER', 'WOMAN', and 'MEMORY' because the eye tracker prevented potential typing errors.

Table 2
Summary of online experimental results of all participants.

Participants	Time to type one character (s)	Total number of typed characters	Number of typos (not prevented)	Number of prevented typos	Ratio of typo prevention (%)	Time saved (s)
P1	3	101	27	21	43.75	63
P2	6	123	36	17	32.08	102
P3	6	106	28	18	39.13	106
P4	6	91	16	9	36.00	54
P5	6	92	18	11	37.93	66
P6	4	85	14	11	44.00	44
P7	5	109	30	18	37.50	90
P8	4	124	44	32	42.11	128
P9	5	97	23	16	41.03	80
P10	4	98	22	13	37.14	52
Average	4.9	102.2	25.8	16.6	39.07	78.5

The eye tracker itself can also be used as a tool for the communication of the disabled [44,45]. For users with normal oculomotor functions, the performance (accuracy and resolution) of the eye tracker-based spelling systems should be better than that of the EEG-based mental spelling systems. In practice, however, many patients with severe ALS have difficulty in moving their eyeballs or blinking their eyes as naturally as normal individuals can [46–48]. For instance, a study by Averbuch-Heller et al. [46] described an ALS patient with normal corrected visual acuity who could move his eyes horizontally, but had difficulty moving them upward. Since these patients cannot control eyeball mouse cursors accurately, many of them cannot use the eye tracker-based speller systems at all. Since fine control of the eyeballs is not necessary to operate independent-type BCI spellers [1], BCI spellers can be alternatively used for the communication of patients with severe neuromuscular disorders. Moreover, spelling systems based on high performance eye trackers are not only generally expensive, but they also require time-consuming calibration processes to initiate the coordinate frames [49]. In this study, we used a low-cost web camera to detect simply the binary horizontal location of the eyeballs (left or right) without any calibration processes. The reference lines in Fig. 2 were empirically determined so that the accuracy of the binary decision of the eye tracker could be 100% when the visual angle of the keyboard was set to 40°. If the visual angle is largely changed, the reference lines also need to be set again; however, this process does not necessarily require a long calibration time if the relationship between the eye tracker accuracy and the visual angle is evaluated preliminarily.

One important factor that might influence the performance of eye-tracking would be the distance between the speller keyboard and the subject, which was set to 44 cm based on our previous study [26]. If some patients feel uncomfortable in staring at LEDs located at such a close distance, the distance needs to be increased. However, the increment of distance will degrade the performance of the eye-tracker because of the reduced visual angle between the webcam and the subject's eyes. Simultaneous use of two webcams for tracking each eye would be one of the potential solutions to tackle this problem, which is an interesting topic that we want to perform in the future study. In addition, it would be also interesting to compare the efficiency of our hybrid spelling paradigm with that of expensive high performance eye-trackers [50,51] in various aspects such as the price performance, preparation time, information transfer rate, and so on.

In the present study, since we adopted a simple classification algorithm that finds the frequency with the largest SSVEP response [25,26,52], the same typing errors occurred repeatedly depending on each participant. Frequencies that elicit strong SSVEP responses are highly dependent upon the participants [53]. In the case of participant P8, three characters, 'M', 'L', and 'I', were mistyped 9, 6, and 5 times, respectively. Although the eye tracker could prevent some typing errors, we are currently considering more advanced classification algorithms such as phase-constrained canonical correlation analysis (p-CCA) [54], as previous studies have demonstrated that the CCA-based classification algorithm could improve the performance of SSVEP-based BCI systems [54–56]. In order to properly apply CCA-based methods, more than eight channels are needed, but we used only three electrodes (Oz, O1, and O2) in the present study. Nevertheless, we are planning to apply CCA-based methods in our future studies to enhance the performance of our system.

Detection of ErrP has been the one of the representative error prevention techniques, and many previous literatures have demonstrated that the ErrP detection can improve the overall performance of various BCI systems [38–41,57,58]. In particular, Combaz et al. [38] and Schmidt et al. [40] developed visual spellers with an automatic error-correction function based on ErrP detection. Recently, Spüler et al. [41] confirmed that ErrP could be used to increase the overall bit rate of a P300-based mental speller. The ErrP-based error correction method has an advantage over our eye-gaze-based error prevention approach in that it can be applied to various speller types regardless of the BCI paradigms such as motor imagery, P300, and SSVEP [38–41,57,58]. However, in contrast to our eye gaze-based error prevention method, the ErrP-based error correction method can detect typing errors only after presenting the mistyped characters on the screen, which spends unnecessary time. Moreover, the ErrP-based error correction method cannot be efficiently applied to some individuals for whom the accuracy of ErrP detection is low. Therefore, it would be an interesting future topic to develop a new technique to combine the ErrP-based error correction method and the proposed hybrid mental speller to enhance the error correction performance.

5. Conclusions

In this study, we introduced a hybrid mental spelling system which prevents additional typing of 'BACKSPACE' to correct typos. In order to detect typos, simultaneously utilizes both EEG signals recorded from the occipital area and the horizontal eye-gaze direction information extracted from a low-cost webcam-based eye tracker. In our online experiments conducted with 10 healthy participants, at least 16.6 typos could be prevented, from the results, verifying that the proposed strategy could effectively enhance the performance of the SSVEP-based mental spelling system.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.bspc.2015.05.012

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